CAUGHT BETWEEN TWO STOOLS?

FOUR ESSAYS ON VALUE CREATION AND VALUE EXTRACTION ON FREE DIGITAL PLATFORMS

Inauguraldissertation zur Erlangung des Doktorgrades des Fachbereichs Wirtschaftswissenschaften an der Wirtschaftswissenschaftlichen Fakultät der Universität Passau

eingereicht von

Sebastian Schubach, M.A. M.Sc.

Passau, Februar 2019

Dissertation an der

Wirtschaftswissenschaftlichen Fakultät

der Universität Passau

Erstgutachter: Prof. Dr. Jan H. Schumann

Lehrstuhl für Betriebswirtschaftslehre mit Schwerpunkt

Marketing und Innovation

Universität Passau

Zweitgutachter: Prof. Dr. Dirk Totzek

Lehrstuhl für Betriebswirtschaftslehre mit Schwerpunkt

Marketing und Services

Universität Passau

Datum der Disputation: 10. Mai 2019

Acknowlegdements

At the end, my dissertation is nothing more than thousands of words that fill numerous, even hundreds of pages. The cognitive meaning of those words will be clear to marketing researchers quickly when reading my dissertation; however, the emotional meaning of those words will be only apparent to those persons, who accompanied me through part of or the whole journey “dissertation”. Therefore, I’d like to take the opportunity and thank those travelling companions.

First and foremost, I want to thank Prof. Dr. Jan H. Schumann, my supervisor, mentor, and boss. He offered me a position as research assistant and doctoral candidate at the Chair of Marketing and Innovation of the University of Passau back in 2013, even if I had no idea at this time what research questions, moderators, mediators, or contributions are. Throughout the years, he did a tremendous job in guiding, supervising, and advising me, so that I now not only hand in my dissertation, but also feel part of the marketing research community. Jan, I highly appreciated your consistent feedback on my research projects (even when going to the Frontiers in Service Gala dinner at Times Square after weeks of hard work and conference presentations) and your intuition about how to tell great research stories. Yet, I am even more grateful that we increasingly worked together as equal partners over the time of my dissertation. Moreover, I am grateful for all the opportunities you created—travelling to international and renowned conferences all over the world, being a visiting scholar at Boston College for several months or organizing conferences with top class speakers from academia and practice, just to name a few. Thanks, Jan!

Second, I want to say thank you to Prof. Dr. Alexander Bleier from Frankfurt School of Management and Finance. As Assistant Professor and co-author, Alex was the perfect person to talk to about my dissertation and current research projects, but also about what happens after the dissertation. As Assistant Professor, Alex was on the one hand close enough to the dissertation to understand the

worries and daily frustrations of a doctoral candidate. On the other hand, Alex was this big step ahead in the academic career, so that he was an important advisor and mentor, sharing his experiences and viewpoints. Thanks so much, Alex, for our joint research work, for having me at Boston College during your time as Assistant there, and for the constant that we always got work done at the (very) last minute. Because we both know: “Irgendwas ist ja immer”!

Third, many thanks goes to all researchers giving me feedback on my work within the review process, during conferences, doctoral consortiums, or workshops, and thus shaping my profile as researcher. Especially, I want to thank my faculty from the 46. EMAC Annual Conference’s Doctoral Consortium in Groningen, Professor Kapil Tuli (Singapore Management University), Professor Katrijn Gielens (UNC Kenan-Flagler Business School) and Professor Aurélie Lemmens (Tilburg University). Through your feedback, I gained confidence and trust in what I was doing in my research projects!

Fourth, many thanks also go to Prof. Dr. Dirk Totzek who agreed to be the second examiner of this dissertation, and to Prof. Dr. Jan Krämer for being the chairperson of my dissertation committee.

Fifth, a big thank you goes to my current and former “teammates” at our Chair. Thanks for your amazing support and the great atmosphere. Thanks, Eva, for being available all the time for my questions (especially in the beginning of my dissertation), but also for our great research discussions and all the seminars we did together. Thanks, Sabine, for all of our joint work, in which we could blindly trust each other. Thanks also for all those conversations about research and the (pains of the) dissertation, may it was in Passau, Shanghai, or New York. Thank you Armin, for giving me the opportunity to work with you as co-author and, thus, to publish early in my academic career. Still fascinating to see what we have put together in just a few weeks. Many thanks to Nicole and Janina for our great conversations about research, teaching, and beyond, but especially for your emotional support

during the (sometimes hard times of the) dissertation. And to the “Bavarian Buam” for great talks and evenings. And, last but not least, to all the student assistants at our Chair for all their work and support that helped me a lot to focus on my research and this dissertation.

Finally, I want to thank the most important persons in my life. Thanks, Tina, for always being by my side. Thank you so much for unconditionally supporting me, for your energy, but also for accepting the times when I was not in the best mood, especially when results didn’t turn out as they should have done. Thank you for putting life into the right perspectives in these moments and for your amazing capability to take my mind off my work (and if that didn’t work out, Charly was still there ;-)). Thank you, Mum and Dad. It is because of you that I am writing these words in this very moment. Thank you for making everything possible for me, for supporting me unconditionally and for being there for me at any time.

Thank you all!

Summary

Free digital platforms constitute one of the most important phenomena of modern times; they create value by bringing together customer groups that would not have interacted without digital technology or that could have done so only by incurring increased costs. In the free digital platform model, firms pay for the interaction with end consumers that use the digital platform for free. Extant research on two-sided markets has provided rich evidence for how digital platforms can attract enough members from both customer groups to enable the interaction between the customer groups. However, this research lacks insights into how free digital platforms can create value for their customer groups once these customer groups joined the platform, and extract this value for themselves.

To address this substantial research gap, in this dissertation, I investigate the overall research question of how activities of free digital platforms affect the value creation for their customer groups and the ability of the platform to extract this value. In a first step, I examine this value creation and value extraction by focusing on concrete activities of free digital platforms. In Study 1, I investigate how offering firms the possibility of personalizing and positioning their search ads on search engines affects consumers' search engine click behavior. In Study 2, I examine how adapting ad positions to consumers' previous online shopping behavior on search engines influences consumers' click and conversion behavior. In Study 3, I investigate the impact of a review platform's policy of tagging reviews as written on either mobile or nonmobile devices on consumers' perceptions of review helpfulness. In a second step, in Study 4, I generalize these findings by investigating the overall impact of such customer-oriented activities on value creation for customer groups and on the extraction of this value by free digital platforms.

These four studies yield three major findings. First, free digital platforms' activities toward one customer group always affect the value creation of the other customer group as well. Second, free digital platforms should emphasize value

creation activities especially for non-paying customer groups. Third, internal, operative, and macro-environments influence the value creation and value extraction of free digital platforms.

With this dissertation, I make substantial contributions to research on two-sided markets, customer orientation, search engine advertising, and online reviews. In addition, my dissertation provides numerous actionable recommendations for managers of free digital platforms and outlines promising avenues for further research.

Table of Contents

1. Introduction

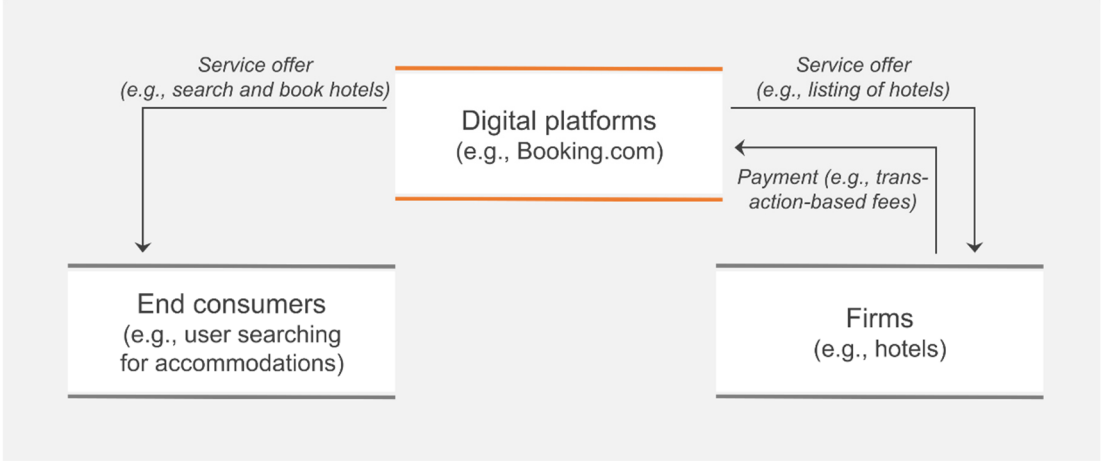
1.1 Digital Platforms: More Than Extrinsic Value Creation

The emergence of digital platforms constitutes one of the biggest and most fundamental changes in business models in the global economy since the Industrial Revolution (Accenture, 2016; Parker, van Alstyne, & Choudary, 2016). Digital platforms are an integral part of our daily lives; we use them when reading online newspapers, searching for information on search engines, browsing through product reviews before purchasing, or booking accommodations for holidays on platforms such as TripAdvisor or Booking.com. Not surprisingly, firms using digital platforms as their businness model represent one of the main drivers of the world's economy. In 2018, Amazon, Alphabet, and Facebook ranked among the 10 most valuable companies worldwide (Shen, 2018). Similarly, more than half of the top 10 listed "unicorns"—start-ups with valuations of $1 billion or more—were digital platforms (Fortune, 2018). By 2020, those platforms are predicted to make up at least one-quarter of the world's economy (Accenture, 2016).

The peculiarity of digital platforms lies in the way they offer value to and extract value from customers (Eisenmann, Parker, & van Alstyne, 2006; Kumar & Reinartz, 2016; van Alstyne, Parker, & Choudary, 2016). Digital platforms offer value to two or more customer groups by enabling interactions between the groups that would not have been possible without the platforms or that would have been very costly (Caillaud & Jullien, 2003; Rochet & Tirole, 2006; van Alstyne et al., 2016). For instance, advertisers connect with end consumers on online news portals; hotels interact with end consumers on online marketplaces such as Booking.com; and end consumers interact with both firms and other end consumers on online review platforms (Figure 1.1). Digital platforms extract value from these interactions by charging customer groups that have the greatest willingness to pay for interaction with other customer groups. In this way, digital platforms fundamentally differ from traditional firms that offer value to customers by purchasing goods from suppliers

and adding value to them through transformation. Thus, traditional firms capture value by selling transformed goods to a single customer group only (Chakravarty, Kumar, & Grewal, 2014; van Alstyne et al., 2016).

Figure 1.1. Exemplary value creation and value extraction of digital platforms



Because of the interactive nature of digital platforms, customer groups are interdependent. This interdependence influences how digital platforms create value and how they extract it. Digital platforms create two types of value. First, they create *extrinsic* value for their customers, that is, benefits derived from outside the product (Lee & O'Connor, 2003). The extrinsic value of a digital platform is higher for one customer group, the more customers of the other group there are on the platform, and vice versa (Armstrong, 2006; Caillaud & Jullien, 2003). Thus, a platform's extrinsic value is closely connected to the concept of network externalities (Katz & Shapiro, 1985). For example, platforms such as Booking.com create value for end consumers only if many hotels participate in the platform, but hotels join the platform only if there are enough end consumers.

Second, digital platforms create *intrinsic* value, benefits derived from platforms' features and content. In particular, digital platforms act as resource integrators; they integrate resources provided by one customer group into value offers to other customer groups (Hillebrand, Driessen, & Koll, 2015; van Alstyne et al., 2016; Vargo & Lusch, 2017). Digital platforms also provide resources to their

customer groups on their own (Hagiu & Spulber, 2013). For example, Booking.com's value proposition to end consumers includes product descriptions and product photos provided by hotels. In turn, end consumers' attention to this content is part of Booking.com's value proposition to hotels. Moreover, Booking.com provides its own resources to customer groups, such as checkout processes or tools for writing reviews.

Given the interdependencies of customer groups in digital platforms, the latter are interested in strategies for how to create both extrinsic and intrinsic value for customer groups and how to extract this value. Extant research has focused mainly on the creation of extrinsic value through network externalities; it emphasizes theoretical models specifying how network externalities influence the successful use of marketing mix elements and also seeks to quantify network effects (Chu & Manchanda, 2016; Rochet & Tirole, 2006). Accordingly, most studies focus on digital platform pricing (Armstrong, 2006; Caillaud & Jullien, 2003; Rochet & Tirole, 2003, 2006). They demonstrate that pricing on digital platforms should follow the "divide-and-conquer" principle, such that platforms subsidize the customer group that exhibit higher network externalities by charging the other customer group. This latter customer group is willing to pay for interaction, because reaching out to the subsidized customer group via digital platforms provides them with high extrinsic value (Caillaud & Jullien, 2003; Rochet & Tirole, 2006). The „divide-and-conquer" principle thus explains the widespread phenomenon of free digital platforms, for which end consumers do not have to pay to access platform content, because firms or paying end consumers subsidize the free offerings (Anderson, 2013). For product marketing and marketing communications, research also demonstrates that digital platforms should target the customer group with higher network externalities (Gupta & Mela, 2008; Kraemer, Hinz, & Skiera, 2010; Tucker & Zhang, 2010; Zhang, Evgeniou, Padmanabhan, & Richard, 2012).

Despite this considerable knowledge about extrinsic value creation, little is known about how digital platforms create intrinsic value by coordinating and offering resources to customer groups (van Alstyne et al., 2016). There is a particular lack of studies about how specific platform activities influence the value creation of platforms' customer groups and the value extraction of the platforms themselves. Chakravarty et al. (2014) offer the first promising evidence; they demonstrate that digital platforms' customer-oriented behaviors toward each of their customer groups have positive effects on the platforms' financial performance, as does asymmetrically distributed customer orientation toward the customer groups when digital platforms are particularly dependent on one of the two customer groups. Although Chakravarty et al. (2014) investigate the influence of platform activities on platforms' ability to capture value, they do not examine in detail how such activities influence the value creation of the platforms' customer groups. That is, the authors do not demonstrate whether and how customer-oriented behaviors toward one customer group influence value creation of the other customer group. Moreover, Chakravarty et al.'s (2014) study does not investigate value creation and extraction related to *free* digital platforms, on which at least one customer group does not have to pay for platform offerings.

However, such investigations are important for two reasons. First, free digital platforms have high managerial relevance. As mentioned, these platforms are widespread in practice, because they are the natural outcome of network externalities present on digital platforms (Eisenmann et al., 2006). They also are highly successful, as demonstrated by the social networks such as Facebook (Facebook Inc., 2016) or Alphabet's search engine Google (Alphabet Inc., 2016). Overall, free digital platforms constitute a multibillion-dollar industry (Anderson, 2013). Second, consumer research shows that free offerings are special in the sense that they lead to irrational consumer behavior. Consumers *overvalue* the benefits of free offers but *underestimate* the costs they incur by accepting the offers,

causing a disproportionally high choice of free offers (Hüttel, Schumann, Mende, Scott, & Wagner, 2018; Shampanier, Mazar, & Ariely, 2007). Accordingly, free offerings may also alter managers' decision-making.

In summary, in the context of free digital platforms, there is a significant gap in literature regarding the impact of platform activities on intrinsic value creation for customer groups and platforms' extraction of this value. This dissertation addresses this gap by conducting four empirical studies in different contexts and referring to different methodological approaches, thereby answering the following overarching research question:

> *How do free digital platforms' activities influence the value they create for their customer groups and the value they extract from their customer groups?*

1.2 Research Objectives and Scope

In Studies 1 to 3, as a first step toward answering this overarching research question, I seek a better understanding of how concrete activities of free digital platforms influence customer groups' value creation and platforms' value extraction. In Studies 1 and 2, I investigate this question in the context of search engines; in Study 3, I focus on the context of online review platforms.

With more than 3.6 million search queries per minute worldwide (Statista, 2018) and almost $50 billion in ad spending (PwC, 2017), search engines constitute one of the most important types of free digital platforms. In search engine advertising, advertisers pay for the ads that search engines display to end consumers in the moments when these consumers are actively searching for purchase-relevant information. Advertisers' objective is to acquire new customers or re-acquire previous customers. Thus, it is possible to investigate the impact of platform activities on both a non-paying (consumers) and a paying customer group

(advertisers) and identify the effects of these activities on a search engine's value extraction.

Next, by focusing on online review platforms in Study 3, I extend the initial evidence from the first two studies to digital platforms with more than one non-paying customer group. On online review platforms, consumers can both write and read reviews for free; firms pay for their listings on the platforms or for platforms' marketing research. Overall, online review platforms have substantial influence on both consumer decision making and the business performance of reviewed firms (Chevalier & Mayzlin, 2006; Yadav & Pavlou, 2014).

1.2.1 Study 1: Personalization or Positioning in Search Engine Advertising? It Depends on Your Competition!

In Study 1, I focus on two search engine features that allow advertisers to personalize their search ads according to consumers' search queries and position their ads on the search engine's results page. Previous research on search engine advertising has shown that personalization and positioning create value for consumers and advertisers (Agarwal, Hosanagar, & Smith, 2011; Narayanan & Kalyanam, 2015; Rutz & Trusov, 2011). However, previous studies do not examine how jointly personalizing and positioning ads affects value creation for both customer groups. Thus, in Study 1, I investigate how personalization and positioning efforts influence the probability that consumers will click on firms' search ads. By clicking on search ads, consumers directly create value for firms that search engines can extract. I also include a competitor's decision to personalize or not personalize its search ad, because competitors' ads appear together with a focal firm's ad in search results and can substantially influence the effectiveness of the focal firm's ad (Animesh et al., 2011). Thus, the research questions of Study 1 are:

> *What is the relationship between personalization and positioning effects? In which conditions is ad personalization more effective than ad positioning, and vice versa?*

> *How do competitors' personalization efforts influence the effectiveness of search ad personalization and positioning?*

1.2.2 Study 2: How Online Shopping Behavior Informs Positioning Strategies in Search Engine Advertising

Study 2 leverages the digital platform Google. Since 2012, a new feature has allowed firms to track consumers' previous behavior in their online stores and adjust search engine advertising accordingly when consumers visit the search engine subsequently. To promote the feature's use, Google recommends strategies to increase the effectiveness of search engine advertising for those consumers. One such recommendation is that firms should segment consumers' previous online shopping behavior into different stages of the buying process and position ads higher for consumers who have advanced further in the buying process (Google, 2016). In Study 2, I investigate this recommendation together with my co-authors, noting that previous research has identified a search ad's position as a main driver of its effectiveness and efficiency (Narayanan & Kalyanam, 2015). Specifically, we examine how ad positions influence consumers' click and conversion responses to search ads, depending on their stage in the buying process. To this end, we use experimental and observational field data that we collected, together with a German search agency and an international multibrand fashion retailer. In Study 2, we seek to answer the following research question:

> *How do ad positions influence consumers' click and conversion behavior in search engine advertising, depending on consumers' stage in the buying process?*

1.2.3 Study 3: "Why Would I Read a Mobile Review?" Device Compatibility Perceptions and Effects on Perceived Helpfulness

In contrast with Studies 1 and 2, Study 3 focuses on online review platforms with two non-paying customer groups and a paying customer group. My co-authors and I leverage the introduction of a cue that characterizes a review as created on a mobile device (i.e., smartphone) or a nonmobile device (i.e., desktop PC, laptop) on a German online review platform. Online review platforms employ such cues so that recipients can assess the specific contexts in which the reviews were written and make better informed decisions (Seave, 2013). Accordingly, extant research demonstrates that cues influence recipients' evaluations of reviews (Forman, Ghose, & Wiesenfeld, 2008; Naylor, Lamberton, & Norton, 2011), but it has not investigated the influence of specific devices. It is important to clarify the devices' impacts though, because consumer behavior on mobile devices differs fundamentally from their behavior on stationary devices (Ghose, Goldfarb, & Han, 2013; Lurie, Ransbotham, & Liu, 2014). Using a field study, a lab experiment, and a field experiment, we investigate how device cues influence recipients' perceptions of helpfulness and thus their created value. We specify whether consumers wrote reviews on mobile or nonmobile devices and whether recipients read the reviews on mobile or nonmobile devices. The research question driving Study 3 is:

> *How does tagging of online reviews as written on mobile or nonmobile devices influence recipients' perceptions of review helpfulness?*

1.2.4 Study 4: Born Free?! How Prior Strategic Commitments Influence Customer Orientation Behaviors and Their Outcomes in Free E-Services

In Study 4, my co-authors and I examine digital platform activities at a more abstract level. According to the idea that customer-oriented behaviors are the basis of value creation (Slater, 1997), we investigate how free digital platforms' customer

orientations influence the value creation of their customer groups and the platforms' value extraction. Research has shown that customer orientation is one of the main drivers of firm performance (Jaworski & Kohli, 1993; Kirca, Jayachandran, & Bearden, 2005; Narver & Slater, 1990). However, to date, it has not provided evidence of how customer orientation behaviors affect value creation and value extraction in the context of free digital platforms. In Study 4, we address this gap using insights from qualitative and quantitative interviews. we also compare the effect of customer orientation on value creation and value extraction for firms that operated free digital platforms from the outset and those that did not. In this regard, both academic and anecdotal evidence has shown that firms that did not start with free digital platforms (e.g., online newspapers) are struggling with this business model (Lambrecht & Misra, 2016; Pauwels & Weiss, 2008; The Economist, 2015). Thus, in Study 4, we seek to answer the following research questions:

> *How does customer orientation toward one customer group affect value creation for this and the other customer group?*

> *How does customer orientation toward the customer groups influence free digital platforms' value extraction?*

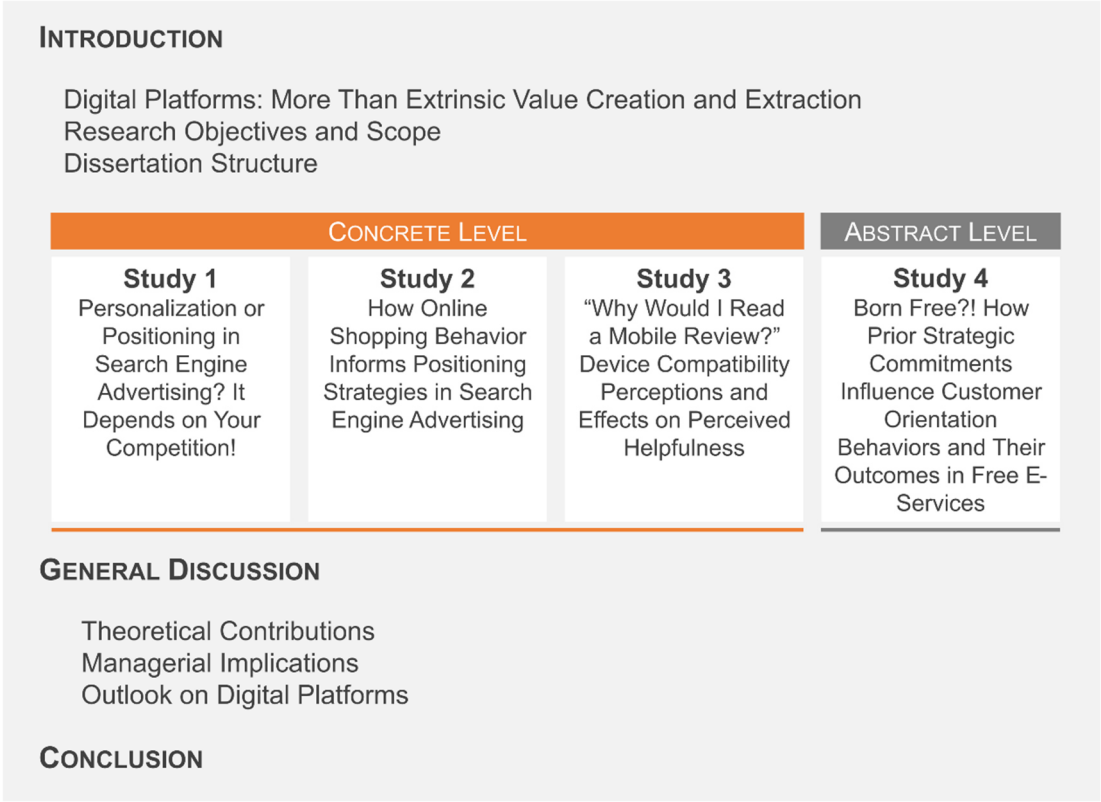
> *How do free digital platforms' prior strategic commitments influence value creation and extraction through customer orientation?*

In sum, my dissertation employs different contexts, data and methods to answer my overarching research question how a free digital platform's activities influence the value creation of their customer groups and the value that they get from their customer groups. Thus, the findings of my dissertation are reliable, valid and generalizable and will make a fundamental contribution to research on digital platforms as well as provide important and actionable implications for marketers.

1.3 Dissertation Structure

The structure of my dissertation is as follows. Chapters 2 to 4 focus on free digital platforms' concrete activities and investigate their influence on value creation and value extraction. Chapter 2 features Study 1, which investigates the impact of personalizing and positioning search ads on the search engine Google. Chapter 3 examines the impact of adjusting keyword bids and search ads' positions to consumers' prior online shopping behavior on search ad effectiveness (Study 2). Chapter 4 introduces Study 3 and focuses on online review platforms to determine the impact of tagging reviews as written on mobile or nonmobile devices on consumers' perceptions of review helpfulness. Chapter 5 concludes with Study 4, in which I examine free digital platforms' activities on a more abstract level and investigate the implications of customer orientation behaviors on customer groups' value creation and a platform's value extraction. Chapter 6 discusses the results of the four studies and derives important implications for research and practice. It concludes with an outlook on digital platforms. Chapter 7 summarizes the findings of my dissertation. Figure 1.2 features the structure of my dissertation.

Figure 1.2. Structure of The Dissertation



1.4 References

Accenture. (2016). People first: Accenture technology vision 2016: People first: The primacy of people in a digital age. Retrieved from https://www.accenture.com/t20160804T100550Z__w__/us-en/_acnmedia/Accenture/Omobono/TechnologyVision/pdf/Technology-Trends-Technology-Vision-2016.pdfla=en#zoom=50

Agarwal, A., Hosanagar, K., & Smith, M. D. (2011). Location, location, location: An analysis of profitability of position in online advertising markets. *Journal of Marketing Research*, *48*, 1057–1073. https://doi.org/10.1509/jmr.08.0468

Alphabet Inc. (2016). Form 10-K for the fiscal year ended December 31, 2016. Retrieved from https://abc.xyz/investor/pdf/20161231_alphabet_10K.pdf

Anderson, C. (2013). *Free: How today's smartest businesses profit by giving something for nothing*. London: Random House.

Animesh, A., Viswanathan, S., & Agarwal, R. (2011). Competing “creatively” in sponsored search markets: The effect of rank, differentiation strategy, and competition on performance. *Information Systems Research*, *22*, 153–169. https://doi.org/10.1287/isre.1090.0254

Armstrong, M. (2006). Competition in two-sided markets. *The RAND Journal of Economics*, *37*, 668–691. Retrieved from http://www.jstor.org/stable/25046266

Caillaud, B., & Jullien, B. (2003). Chicken & egg: Competition among intermediation service providers. *The RAND Journal of Economics*, *34*, 309–328. https://doi.org/10.2307/1593720

Chakravarty, A., Kumar, A., & Grewal, R. (2014). Customer orientation structure for internet-based business-to-business platform firms. *Journal of Marketing*, *78*, 1–23. https://doi.org/10.1509/jm.12.0442

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, *43*, 345–354. https://doi.org/10.1509/jmkr.43.3.345

Chu, J., & Manchanda, P. (2016). Quantifying cross and direct network effects in online consumer-to-consumer platforms. *Marketing Science*, *35*, 870–893. https://doi.org/10.1287/mksc.2016.0976

The Economist. (2015). Up against the paywall. Retrieved from https://www.economist.com/news/business/21678799-many-publishers-still-see-little-alternative-continual-cutbacks-up-against-paywall

Eisenmann, T., Parker, G., & van Alstyne, M. W. (2006). Strategies for two-sided markets. *Harvard Business Review*, *84*, 92–101.

Facebook Inc. (2016). Facebook annual report 2016. Retrieved from https://s21.q4cdn.com/399680738/files/doc_financials/annual_reports/FB_AR_2016_FINAL.pdf

Forman, C., Ghose, A., & Wiesenfeld, B. (2008). Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. *Information Systems Research*, *19*, 291–313. https://doi.org/10.1287/isre.1080.0193

Fortune. (2018). The unicorn list. Retrieved from http://fortune.com/unicorns/

Ghose, A., Goldfarb, A., & Han, S. P. (2013). How is the mobile internet different? Search costs and local activities. *Information Systems Research*, *24*, 613–631. https://doi.org/10.1287/isre.1120.0453

Google. (2016). Reach the right audiences with RLSA: Google best practices. Retrieved from https://support.google.com/adwords/answer/6167113

Gupta, S., & Mela, C. F. (2008). What is a free customer worth? Armchair calculations of nonpaying customers' value can lead to flawed strategies. *Harvard Business Review*, *86*, 102–109.

Hagiu, A., & Spulber, D. (2013). First-Party content and coordination in two-sided markets. *Management Science*, *59*, 933–949. https://doi.org/10.1287/mnsc.1120.1577

Hillebrand, B., Driessen, P. H., & Koll, O. (2015). Stakeholder marketing: Theoretical foundations and required capabilities. *Journal of the Academy of Marketing Science*, *43*, 411–428. https://doi.org/10.1007/s11747-015-0424-y

Hüttel, B. A., Schumann, J. H., Mende, M., Scott, M. L., & Wagner, C. J. (2018). How consumers assess free e-services: The role of benefit-inflation and cost-deflation effects. *Journal of Service Research*, *21*, 267–283. https://doi.org/10.1177/1094670517746779

Jaworski, B. J., & Kohli, A. K. (1993). Market orientation: Antecedents and consequences. *Journal of Marketing*, *57*, 53–70. https://doi.org/10.2307/1251854

Katz, M. L., & Shapiro, C. (1985). Network externalities, eompetition, and compatibility. *American Economic Review*, *75*, 424–440.

Kirca, A. H., Jayachandran, S., & Bearden, W. O. (2005). Market orientation: A meta-analytic review and assessment of its antecedents and impact on performance. *Journal of Marketing*, *69*, 24–41. https://doi.org/10.1509/jmkg.69.2.24.60761

Kraemer, T., Hinz, O., & Skiera, B. (2010). Return on marketing investments in two-sided markets. Retrieved from http://www.anzmac2010.org/proceedings/pdf/anzmac10Final00236.pdf

Kumar, V., & Reinartz, W. (2016). Creating enduring customer value. *Journal of Marketing*, *80*, 36–68. https://doi.org/10.1509/jm.15.0414

Lambrecht, A., & Misra, K. (2016). Fee or free: When should firms charge for online content? *Management Science*, *63*, 1150–1165. https://doi.org/10.1287/mnsc.2015.2383

Lurie, N. H., Ransbotham, S., & Liu, H. (2014). *The characteristics and perceived value of mobile word of mouth* (Marketing Science Institute Working Paper Series No. 14). Retrieved from http://www.msi.org/reports/the-characteristics-and-perceived-value-of-mobile-word-of-mouth/

Narayanan, S., & Kalyanam, K. (2015). Position effects in search advertising and their moderators: A regression discontinuity approach. *Marketing Science*, *34*, 388–407. https://doi.org/10.1287/mksc.2014.0893

Narver, J. C., & Slater, S. F. (1990). The effect of a market orientation on business profitability. *Journal of Marketing*, *54*, 20–35. https://doi.org/10.2307/1251757

Naylor, R. W., Lamberton, C. P., & Norton, D. A. (2011). Seeing ourselves in others: Reviewer ambiguity, egocentric anchoring, and persuasion. *Journal of Marketing Research*, *48*, 617–631. https://doi.org/10.1509/jmkr.48.3.617

Parker, G., van Alstyne, M. W., & Choudary, S. P. (2016). *Platform revolution: How networked markets are transforming the economy - and how to make them work for you* (First edition). New York, London: W.W. Norton & Company.

Pauwels, K., & Weiss, A. (2008). Moving from free to fee: How online firms market to change their business model successfully. *Journal of Marketing*, *72*, 14–31. https://doi.org/10.1509/jmkg.72.3.14

PwC. (2017). IAB internet advertising revenue report: 2017 full year results. Retrieved from https://www.iab.com/wp-content/uploads/2018/05/IAB-2017-Full-Year-Internet-Advertising-Revenue-Report.REV2_.pdf

Rochet, J.-C., & Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*, *1*, 990–1029. https://doi.org/10.1162/154247603322493212

Rochet, J.-C., & Tirole, J. (2006). Two-sided markets: A progress report. *The RAND Journal of Economics*, *37*, 645–667. https://doi.org/10.1111/j.1756-2171.2006.tb00036.x

Rutz, O. J., & Trusov, M. (2011). Zooming in on paid search ads—A consumer-level model calibrated on aggregated data. *Marketing Science*, *30*, 789–800. https://doi.org/10.1287/mksc.1110.0647

Seave, A. (2013). How TripAdvisor grows scale and network effects: Expertise in gathering UGC. Retrieved from https://www.forbes.com/sites/avaseave/2013/06/20/how-tripadvisor-grows-scale-and-network-effects-expertise-in-gathering-ugc/#1fd5dc2c50ef

Shampanier, K., Mazar, N., & Ariely, D. (2007). Zero as a special price: The true value of free products. *Marketing Science*, *26*, 742–757. https://doi.org/10.1287/mksc.1060.0254

Shen, L. (2018). Here are the fortune 500's 10 most valuable companies. Retrieved from http://fortune.com/2018/05/21/fortune-500-most-valuable-companies-2018/

Slater, S. F. (1997). Developing a customer value-based theory of the firm. *Journal of the Academy of Marketing Science*, *25*, 162. https://doi.org/10.1007/BF02894352

Statista. (2018). Done in 60 seconds. Retrieved from https://www.statista.com/chart/13157/what-happens-in-the-digitalized-world-in-one-minute-in-2017/

Tucker, C., & Zhang, J. (2010). Growing two-sided networks by advertising the user base: A field experiment. *Marketing Science*, *29*, 805–814. https://doi.org/10.1287/mksc.1100.0560

Van Alstyne, M. W., Parker, G., & Choudary, S. P. (2016). Pipelines, platforms, and the new rules of strategy. *Harvard Business Review*, *94*, 54–62.

Vargo, S. L., & Lusch, R. F. (2017). Service-dominant logic 2025. *International Journal of Research in Marketing*, *34*, 46–67. https://doi.org/10.1016/j.ijresmar.2016.11.001

Yadav, M. S., & Pavlou, P. A. (2014). Marketing in computer-mediated environments: Research synthesis and new directions. *Journal of Marketing*, *78*, 20–40. https://doi.org/10.1509/jm.12.0020

Zhang, K., Evgeniou, T., Padmanabhan, V., & Richard, E. (2012). Content contributor management and network effects in a UGC environment. *Marketing Science*, *31*, 433–447. https://doi.org/10.1287/mksc.1110.0639

2. Study 1: Personalization or Positioning in Search Engine Advertising? It Depends on Your Competition!

Sebastian Schubach

Will be submitted to *Marketing Letters* (VHB Ranking: B)

Search engine advertising (SEA) continues to be the most important channel in online marketing, accounting for almost $88 billion in retailers' ad spending. Accordingly, extant research has provided numerous evidences on which SEA strategies are most effective, thereby especially highlighting the importance of ad personalization and ad positioning. Interestingly, however, research on SEA lacks findings on the effectiveness of applying both strategies simultaneously, and how a competitor's decision whether to personalize or not alters a focal ad's effectiveness. Addressing this gap in research, the findings of two laboratory experimental studies with a fictive search engine demonstrate that ad personalization effects dominate ad positioning effects in SEA. As such, personalizing one's ad is usually more effective than not personalizing. Only if surrounding competitors use the same personalization strategy as the focal retailer, the importance of ad positioning becomes salient. Then, higher ad positions outperform lower ad positions, and thus are more effective. These findings offer new theoretical insights in SEA strategies' effectiveness and provide actionable managerial insights.

2.1 Introduction

Firms continue to spend the major share of their online advertising budgets on search engine advertising (SEA), devoting almost 50 percent of all spending ($88 billion) to this advertising format (PwC, 2017; Statista, 2017). With SEA, firms aim to engage with consumers at the moment they actively seek purchase-relevant information on search engines, using either stationary or mobile devices. This form of advertising requires firms to define keywords that consumers are most likely to use to search for products or services. For given keywords, firms assign corresponding search ads and place maximum bids on each keyword. When a consumer submits a search query to the search engine, the search engine runs an auction, with all firms bidding on the keywords contained in the search query. According to a firm's maximum bid on a keyword, the quality score of the corresponding search ad, and competitors' maximum bids, the search engine decides whether and in which position the firm's ad will appear in the search results. Given firms' large investments in SEA, it is of utmost importance for them to understand how to design SEA activities (e.g., keyword selection, ad design, ad positioning) to win their competitive bids and obtain consumer clicks and conversions.

By analyzing primarily observational data, SEA research yields important evidence of effective SEA strategies. It identifies which keywords consumers use and which keywords are most likely to result in clicks and conversions (Klapdor, Anderl, Wangenheim, & Schumann, 2014; Rutz & Bucklin, 2011; Rutz, Bucklin, & Sonnier, 2012). Furthermore, SEA research has widely examined ad design elements that drive consumers' click behaviors (Haans, Raassens, & van Hout, 2013; Rutz & Trusov, 2011) and determined the effectiveness of distinct ad positions (Agarwal, Hosanagar, & Smith, 2011; Ghose & Yang, 2009; Narayanan & Kalyanam, 2015). Notably, scholars cite ad personalization and positioning as the main drivers of ad effectiveness. Rutz and Trusov (2011) show that personalized ad

copy that incorporates consumers' search queries yields higher click probabilities than copy that does not. Ghose and Yang (2009) and Agarwal et al. (2011) determine that ads in higher positions in search engine results have higher click probabilities.

However, such research investigates ad personalization and positioning in isolation; it has not provided insights into whether or how ad personalization and positioning together influence ad effectiveness. Moreover, it has not determined how competitors' decisions to personalize ads affect the relationship between ad personalization and positioning of a focal firm's ads, even though competitors' ads are known to have an important influence (Animesh, Viswanathan, & Agarwal, 2011).

Noting this research gap, there is need for additional scholarly work that provides evidence on how to leverage effective, efficient personalization and positioning in SEA. Accordingly, I use consumer search theory to address the following research questions: What is the relationship between personalization and positioning effects? In which conditions is ad personalization more effective than ad positioning, and vice versa? And how do competitors' personalization activities influence the relevance of ad personalization and positioning effects for a focal firm?

I conduct two laboratory experimental studies to answer these questions. Both experiments employ a fictive search engine with varying personalization and positioning of a focal firm's ad and personalization of competitors' ads. The results show that when competitors do *not* personalize their ads, personalization of a focal firm's ad is more effective than positioning of the ad; that is, ads in higher positions do not yield more clicks than ads in lower positions. However, if competitors *do* personalize their search ads, ad positioning becomes more relevant than ad personalization; consumers are more likely to click on ads that are displayed in high positions than in low positions. The superiority of personalized ads over non-

personalized ads is therefore contingent on ad positioning. Only if personalized ads appear at the top of the search results do they outperform non-personalized ads.

This research makes important contributions to SEA research and provides actionable insights for SEA practice. It deepens scholarly understanding of SEA strategies by demonstrating that ad personalization and ad positioning act independently of each other. Moreover, the results show that personalization and position effects hinge on competitors' ad content decisions. In this sense, this research extends prior studies that reveal isolated effects of ad personalization (Agarwal et al., 2011; Ghose & Yang, 2009; Rutz & Trusov, 2011) but did not investigate how they act together or how competitors' ads influence this relationship. My study results show that ad personalization is effective only when it differentiates a focal ad from a competitor's ad; as soon as competitors also personalize their ads, ad positioning begins to drive search ad effectiveness. The finding suggests that consumers rely on ad positions as decision-making criteria only if they cannot use ad content to differentiate between a focal firm's ad and competitors' ads; it corroborates and extends research by Animesh et al. (2011), who show that unique selling propositions (USP) that focus on either price or quality USPs lose their effectiveness as soon as competitors use the same USPs. However, these authors do not provide evidence about whether ad positions become consumers' main criteria for deciding whether to click on ads in this situation.

The results of my research also allow practitioners to leverage their ad personalization and ad positioning tactics in SEA more effectively and efficiently. If a focal firm's competitors display mainly non-personalized search ads, it is sufficient for the firm to personalize its ads; it does not need to engage in costly auctions (Ghose & Yang, 2009) to gain for top positions in search engine results. However, the firm must engage in such investments if competitors personalize their ads, because in this case, ad positioning becomes a distinctive feature. In this case, ad personalization is important only in top positions; for lower ad positions, it has *no*

additional effect, such that firms can save keyword management costs that stem from having unique ads for each keyword (Amaldoss, Jerath, & Sayedi, 2016).

Section 2 provides a brief explanation of how firms can personalize and position search ads on search engines. It also provides a brief overview of relevant research. Section 3 presents the conceptual framework and research hypotheses, according to consumer search theory. Section 4 contains the results of the two experimental studies, discussed in Section 5. This article concludes in Section 6.

2.2 Theoretical Background

Extant research on SEA has shown that ad personalization and positioning are key drivers of ad effectiveness (Ghose & Yang, 2009; Narayanan & Kalyanam, 2015; Rutz & Trusov, 2011). In the following, I explain how firms can personalize and position their ads on search engines. Moreover, I outline important research in this area.

2.2.1 Personalization of search ads.

Search engines such as Google allow firms to personalize their ads by inserting consumers' search queries in ad copy through placeholders. Firms can use these placeholders in the headers, URLs, or body text of search ads. When a consumer submits a search query, the search engine automatically fills the placeholder with this search query. From Google's viewpoint, matching a firm's ad with consumers' search query helps advertisers render their search ads more relevant for consumers, because search ads capture a consumers' articulated search intention (Google, 2018b).

Rutz and Trusov (2011) support this intuition empirically. Their study demonstrates that search ads that integrate consumers' search queries in headers have higher click probabilities than search ads without search queries in the headers. Klapdor et al. (2014) elaborate on this finding. They reveal that consumers

with specific search intentions especially value personalized search ads. Such ads match the consumers' search intentions, thus facilitating their online shopping. In contrast, when search intentions are less specific, the value of personalized search ads is lower, because non-specific search queries are matched with non-specific ads. As a result, personalized ads do not help consumers reach their shopping goals. Moreover, SEA research suggests that advertising firms incur higher costs when personalizing their search ads, because they must create unique ads for each of their keywords. If they decide not to personalize, they can save costs by employing one ad for multiple keywords (Amaldoss et al., 2016).

2.2.2 Positioning of search ads.

Search engines enable firms to position their ads in search engine results by bidding on keywords. As soon as a consumer submits a search query to a search engine, the search engine runs an auction, with all firms bidding on the keywords contained in the search query. The firm with the highest product of the keyword's bid and quality score—the "ad rank"—wins the auction, such that its ad is displayed in the first position. The remaining ads are assigned to the remaining positions in decreasing order of ad rank, such that the ad of the firm with the second-highest ad rank appears in the second position, the ad with the third-highest ad rank in the third position, and so on. When a consumer clicks on a firm's ad, the firm must pay the price that would have been necessary just to outbid the next-best competitor in the position below. Research has shown that top positions are, in general, highly attractive for firms, because consumers are more likely to click on search ads in higher than lower positions; yet they also incur higher costs when aiming for those top positions (Agarwal et al., 2011; Ghose & Yang, 2009; Narayanan & Kalyanam, 2015).

Research also outlines important boundary conditions that strengthen, weaken, or even reverse positioning effects; such effects depend on several factors,

including whether consumers submit generic, brand-related, or firm-related keywords (Ghose & Yang, 2009; Narayanan & Kalyanam, 2015); firm size (Jeziorski & Moorthy, 2018; Narayanan & Kalyanam, 2015); the firm's focus on quality as opposed to price in the ad copy (Animesh et al., 2011); days of the week; and consumers' prior experiences with given keywords (Narayanan & Kalyanam, 2015).

2.2.3 Personalization, positioning, and competition.

In sum, research in SEA has provided rich evidence on personalization and position effects as well as their boundary conditions. However, and most interestingly, it lacks insights on how the two key drivers of search ad effectiveness (i.e., personalization and positioning) affect ad effectiveness when firms employ both strategies simultaneously. Moreover, evidences on how personalization and position effects depend on competitors' SEA strategies are also missing. In this regard, we only know from previous research that a competitor's specific ad content alters the effectiveness of a focal search ad (Animesh et al., 2011). In particular, a focal firm's quality or price USP loses its effectiveness as soon as competitors employ the same USP in their ads. Therefore, the current research aims to investigate how a competitor's decision to personalize or not personalize its search ads influences the effectiveness of a focal firm's personalization and positioning strategies, using consumer search theory to derive the conceptual framework.

2.2.4 Search engines and consumers search theory.

Displaying search results in rank order leads consumers to evaluate search ads sequentially, i.e., one search ad after the other (Animesh et al., 2011). Consumer search theory has indicated that in sequential search, consumers evaluate for each alternative whether the expected net utiliy of inspecting the upcoming alternatives is higher than the utility of the previously and currently inspected alternatives. Thereby, the expected net utility of inspecting upcoming

alternatives results from the probability of encountering alternatives with high (or low) utility, the utility of each of the upcoming alternatives and costs consumers incur to inspect the upcoming alternatives (Ratchford, 1982; Weitzman, 1979). If alternatives are ranked according to how well they fit to consumers' preferences, the probability of inspecting an alternative with high utility decreases with each alternative inspected in the sequence (Dellaert & Häubl, 2012). Consumers terminate their search as soon as the expected net utility is lower than the utility of the inspected alternatives and choose the inspected alternative with the highest utility (Ratchford, 1982; Weitzman, 1979).

On search engines, consumers assess the utility of paid search results based on how well they meet their search intention (Broder, 2002; Rangaswamy, Giles, & Seres, 2009). The utility derived from search ads is higher the better the search engine assesses the information need behind consumers' search queries. Previous research indicates that advertisers can meet consumers' search intent by matching their search ads to consumers' search queries (Klapdor et al., 2014; Rutz & Trusov, 2011). Moreover, consumers have learnt that search engines display the ads that are most relevant to consumers' search queries mainly in the top positions (Agarwal et al., 2011; Dou, Lim, Su, Zhou, & Cui, 2010). The probability of encountering a search result with high utility therefore decreases with each position on the results page. In summary, personalization (i.e., matching search ads to consumers' search queries) and positioning of search ads determine the utility of paid search ads and, thus, consumers' decision to click on those ads. In the following paragraph I outline in detail, how consumers will determine whether to click on a personalized (non-personalized) search ad in higher (lower) positions in two distinct competitive environments: (1) a non-personalized competitive environment (i.e., in which competitors opt not to personalize their search ads), and (2) a personalized competitive environment (i.e., in which competitors personalize their search ads).

2.3 Conceptual Framework

In general, I assume that consumers search until they encounter the *first personalized* search ad in the search results, independent of its position. They terminate their search at this point and click on this personalized search ad for two reasons: First, consumers choose a *personalized* over a non-personalized ad, as personalized ads better match to consumers' search intention. Second, consumers are more likely to click on the *first* personalized search ad, because the probabability that subsequent search ads have similar or higher utility decreases due to the rank-ordering of search results. In contrast, consumers will not click on the first search ad per se. Even if the probabilitiy of search ads with similar or higher utility also decreases when non-personalized search ads appear high in the search results, the utility of these non-personalized search ads is too low so that the expected net utility of inspecting the upcoming search ads is still higher. Therefore, consumers have an incentive to continue their search and not to click on non-personalized search ads in the top positions. They search until they find the first personalized search ad. Based on this reasoning, I assume the following for a focal firm's personalization and positioning activities in a non-personalized and non-personalized comeptitive environment.

2.3.1 Personalization and position effects in a non-personalized competitive environment.

If the focal firm *personalizes* its search ads while *competitors do not personalize*, consumers will click on the focal ad independent of its position in the research results. When the focal ad appears higher in the search results, the probability for consumers to find a search ad with higher utility is low, such that consumers terminate their search and immediately click on the focal ad. When the ad appears in lower positions, consumers will search until they reach this

personalized ad as it has higher utility than competitors' non-personalized ad that consumers' have searched through before.

However, when the firm decides *not* to personalize its focal ad, I propose that ad positioning regains importance and drives consumers' click probabilities. In this situation, none of the advertisers personalizes its ads to consumers' search queries. Consumers will search through the entire listing of search ads, looking for personalized search ads that provide high utility. None of the ads meets consumers' initial search intentions, though, because they are not personalized. Assuming that consumers ultimately click on one of the ads, they will choose the best available alternative (Parker & Schrift, 2011). Since consumers have learned that search ads in top positions better fit to their own preferences (Agarwal et al., 2011; Dou et al., 2010), non-personalized ads in higher positions are the best available alternative, so that consumers will click on them. Thus, I hypothesize:

H_{1a}: In a non-personalized competitive environment, a personalized focal ad leads to higher click probability than a non-personalized focal ad in both high and low positions.

H_{1b}: In a non-personalized competitive environment, a higher position of a focal ad leads to higher click probability than a lower position only for a non-personalized focal ad.

2.3.2 Personalization and positioning effects in a personalized competitive environment.

In a personalized competitive environment, firms reap the benefits of personalization only in higher, not lower, ad positions, because personalized ads have higher utility than non-personalized ads. However, if focal ads appear in lower positions in the search results, personalized ads to not outperform non-persaonlized ads, as consumers have encountered and clicked on competitors' personalized ads in higher positions in the search results.

Moreover, I assume that positions effects are only important if the focal firm personalizes its ads. If the personalized focal ad appears in the top position,

consumers have a high probability to click on it because it is the first personalized ad they encounter. If the personalized ad appears in the lower positions, consumers will have clicked on competitors' personalized ads, though. Thus, higher positions yield higher click probabilities than lower positions. However, the probability of clicking on a non-personalized focal ad is independent of whether it appears in higher or lower positions. If the non-personalized ad appears in the first position, consumers will not click on the ad and continue their search, as the search ad provides only little utility to consumers. If the non-personalized ad appears in a lower position, consumers will not click on it, because they will have clicked on the *previously encountered* personalized ads that met their search intentions. Thus, I hypothesize:

H_{2a}: In a personalized competitive environment, a personalized focal ad leads to higher click probability than non-personalized ads only in higher positions.

H_{2b}: In a personalized competitive environment, higher position of a focal ad leads to higher click probability than lower position only for a personalized focal ad.

2.4 Lab Experiments

I conducted two lab experiments to examine the effects of personalization and positioning of a focal firm's ad on consumers' clicking behavior. In Study 1, I examine these effects in a non-personalized competitive environment; in Study 2, I examine them in a personalized competitive environment.

2.4.1 Method.

2.4.1.1 Design and participants.

In both studies, I employed a 2 (personalization: yes/no) × 2 (positioning: high/low) between-subjects design. Undergraduate business students from a U.S. college participated for course credit. I followed the same procedure in both lab studies; however, in Study 1, I assessed the proposed effects in a non-personalized

competitive environment, and in Study 2, I assessed them in a personalized competitive environment. To avoid biases, I directed that respondents who took part in Study 1 could not take part in Study 2.

2.4.1.2 Procedure.

At the beginning of the experiment, I asked participants to imagine themselves in a typical online purchasing situation, searching for running shoes and starting their search by using Google. After participants read the vignette, I directed them to select 2 to 4 keywords freely from of a list of 32 carefully selected keywords that consumers would typically employ when searching for running shoes (Table 2.1).

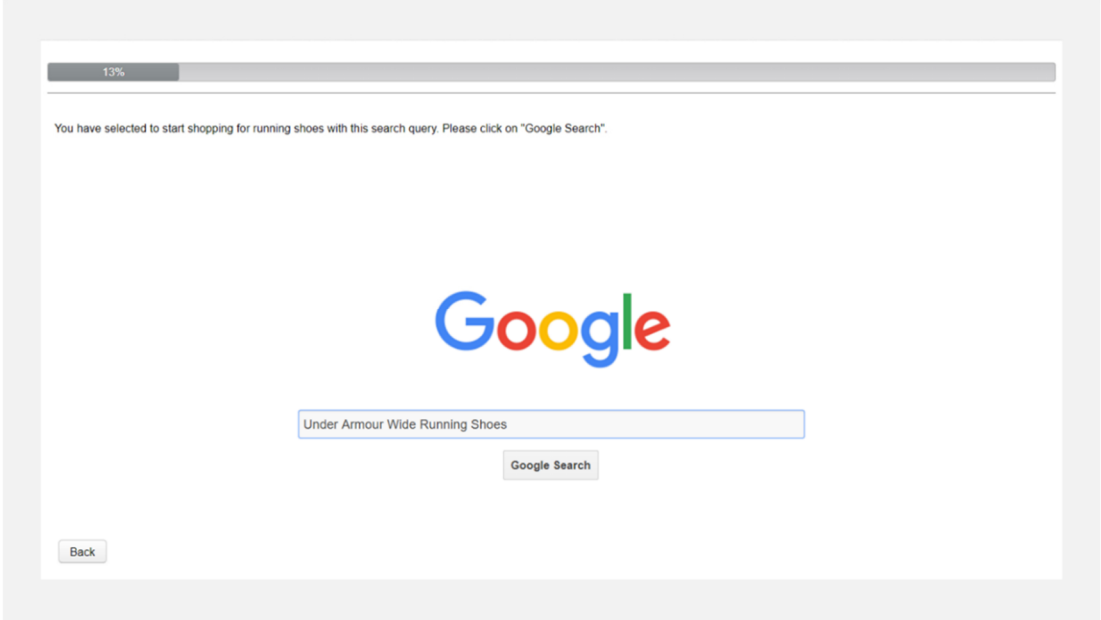
Table 2.1. List of keywords

Type	Brand	Category	Attribute
running shoes	Nike	neutral	high arch
trail	Adidas	stability	low arch
road	New Balance	motion control	narrow
	Under Armour	barefoot	regular
	Saucony	super-cashioned	wide
	Brooks	long distance	light
	Asics	short distance	heavy
	Newton Running		strong damping
	Mizuno		weak damping
	HOKA		high offset
	Pearl Izumi		low offset

I used this pre-defined list of keywords, instead of allowing participants to freely type in search queries, for two reasons. First, it ensured that participants did not enter unrealistic search queries. Second, it enabled me to personalize search ads in a lab experimental setting. The list included keywords of various types (e.g., road running shoes, trail running shoes), categories (e.g., neutral, barefoot, stable), brands (e.g., Nike, Adidas) and attributes (e.g., wide, narrow, light). The variety of keywords makes the experiment more realistic and valid. After participants selected their keywords, their final search queries were displayed in the typical search bar of Google's home page (Figure 2.1). Participants could then check their search

queries, revise them, or submit them to the search engine by clicking on the “Google Search” button.

Figure 2.1. Participant’s search query inserted in Google’s search bar



After submitting their search queries to the search engine, participants received a typical results page with four search ads (Figure 2.2). I asked participants to click on the ad they would be most likely to select. I had three rationales for displaying four search ads. First, four is the maximum number of paid search ads that the search engine displays above organic search results, especially when competition for a keyword is high (Google, 2018a). Second, the ads are viewable at first sight on a stationary device. Third, research has shown that positioning effects are most relevant in those four top positions (Agarwal et al., 2011; Narayanan & Kalyanam, 2015).

To eliminate brand- and ad-specific effects, the ads displayed only fictive brand names (StoreA.com, StoreB.com, StoreC.com, and StoreD.com). They all had the same structure, consisting of a headline, a URL pointing to the landing page in the firm’s online shop, and a description line. The search ad for StoreA.com served as the focal ad, for which I manipulated personalization and positioning. To

manipulate personalization of StoreA.com's ad, I followed Rutz and Trusov's (2011) suggestion and incorporated the participant's submitted search query in the headline of StoreA.com's ad. I strengthened this personalization manipulation by integrating the search query into the URL. In contrast, in the non-personalization condition, I used "Sports Shoes and Apparel" instead of the participant's search query in the headline. Accordingly, none of the 32 keywords on the keyword list appeared in the non-personalized ad of StoreA.com, so participants would not perceive the ad as personalized to their search queries. The URL of the non-personalized ad followed the same structure. I manipulated positioning by displaying StoreA.com's ad either in the first of the four slots (i.e., high position condition) or in the last of the four slots (i.e., low position condition). I randomly assigned the ads of the three other firms to the remaining positions to avoid positioning effects of the competitors' ads.

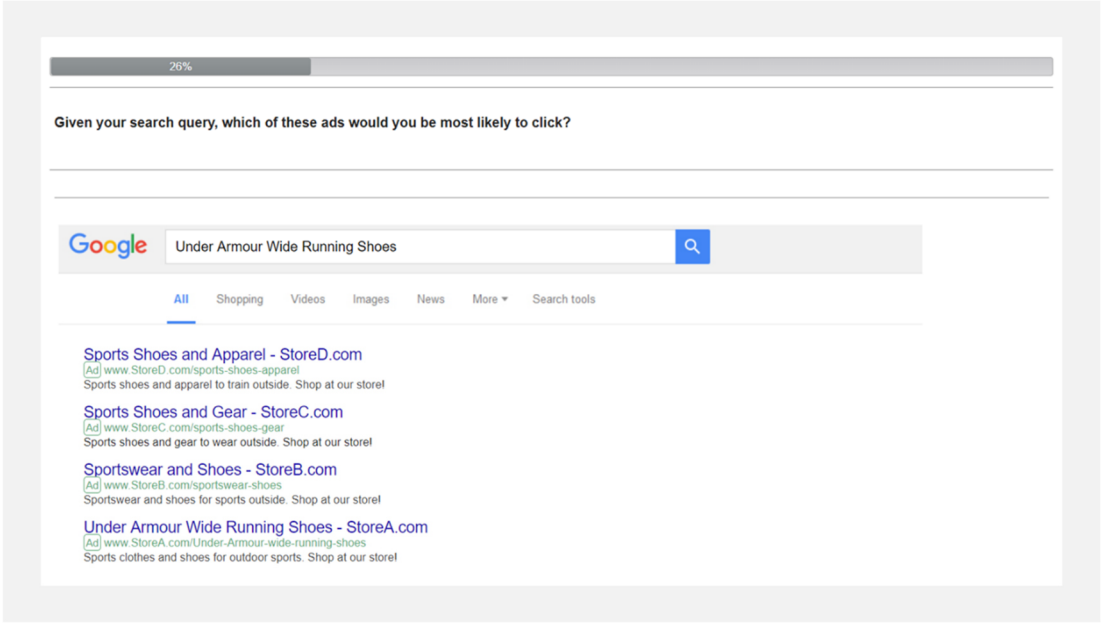
To personalize competitors' ads, I employed the same personalization manipulations used for the focal ad. Competitors' personalized ads integrated each participant's search query into the ad copy's headline and URL; for competitors' non-personalized ads, I created headlines and URLs, which did not include any of the 32 keywords on the keyword list. The headlines and URLs of all non-personalized ads were slightly different, thereby rendering paid search ads realistic and minimizing potential confounding effects. For the description lines, I proceeded in the same way. Figure 2.2 illustrates a personalized ad of StoreA.com in a non-personalized environment (Panel A) and a non-personalized ad of StoreA.com in a personalized environment (Panel B).

After participants clicked one of the ads displayed on the results page, I showed them the same four ads on the next page of the online experiment. I asked them to evaluate StoreA.com's ad again. Subsequently, I asked them to indicate the fit of the search ad with the search query on three 7-point semantic differential items anchored by "bad/good," "inconsistent/consistent," and "not well-aligned/well-aligned" (Roehm & Roehm, 2011). Furthermore, I asked them to indicate their

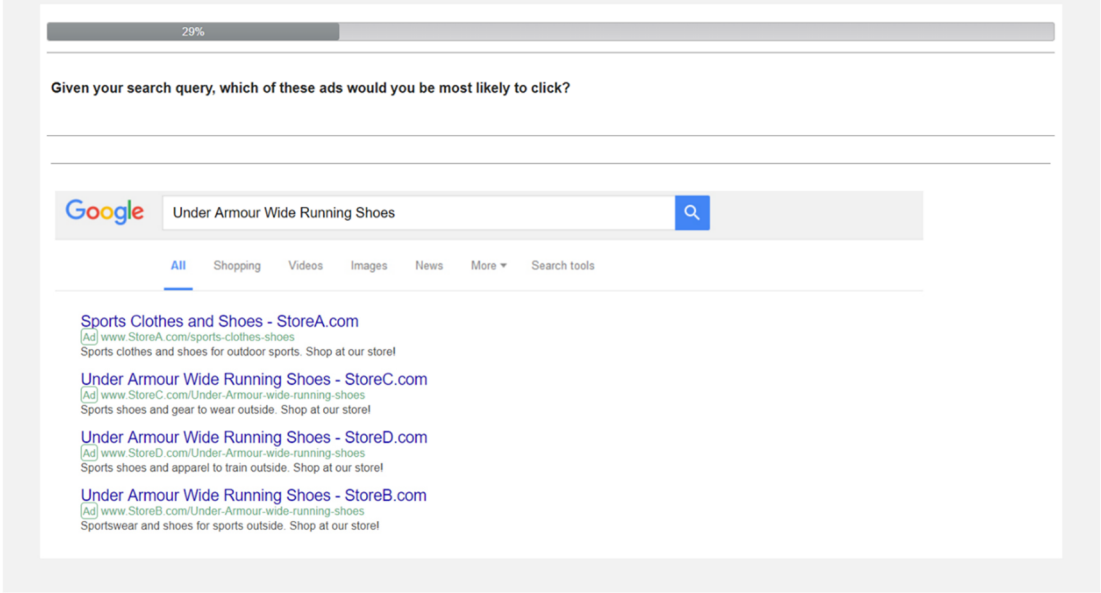
product involvement with running shoes, using Zaichkowsky (1994)'s personal involvement inventory. The inventory consists of twenty 7-point semantic differentials anchored, for example, by "irrelevant/relevant," "means a lot to me/means nothing to me," or "useless/useful." Finally, participants reported their age, gender, and whether they were native English speakers. These elements served as control variables.

Figure 2.2. Exemplary search results pages

Panel A. Personalized ad of StoreA.com in position 4 in a non-personalized environment



Panel B. Non-personalized ad of StoreA.com in position 1 in a personalized environment



2.4.1.3 Dependent variable.

The dependent variable was binary and indicated whether a participant clicked on StoreA.com's ad (= 1) or not (= 0). Clicks on the competitive ads (i.e., StoreB.com, StoreC.com, StoreD.com) constituted non-clicks on StoreA.com's ad and were not further differentiated.

2.4.2 Data.

In total, 161 participants took part in Study 1 (60.9% women; M_{age} = 20.5 years), and 156 (32.5% women; M_{age} = 20.5 years) took part in Study 2.

Table 2.2 shows the distribution of participants' clicks on on the four ad slots on the search results page. Column 1 (i.e., non-personalized competitive environment) reveals that in general, participants clicked on ads in the first position. The number of clicks decreased with each position further down the search engine's results, except for the condition in which the personalized ad for StoreA.com appeared in the fourth position. In this condition, the last ad generated 29 clicks. In a personalized competitive environment (column 2), it was also the first position to get most of the clicks. The number of clicks decreased with each further position, except

in the condition in which the non-personalized ad of StoreA.com appeared in the first position. In this case, it was the ad in the second position, not the first, that attracted the most clicks.

This distribution of clicks confirms my theoretical reasoning that consumers will search until they encounter the first personalized ad and click on it, no matter whether it is the focal personalized ad or a competitor's ad. When more than one ad is personalized, most consumers will click on the ad in the first position. To assess the significance of these descriptive personalization and positioning results, in the next section, I use two logistic regressions, one for each competitive environment.

Table 2.2. Distribution of clicks for experimental conditions across positions

	Competitive ads							
	(1) Non-personalized				(2) Personalized			
Click in position	P1	P4	NP1	NP4	P1	P4	NP1	NP4
1st position	33	6	11	18	23	20	13	26
2nd position	6	4	11	10	11	10	18	4
3rd position	0	1	7	8	4	2	5	5
4th position	2	29	11	4	1	6	3	2
Total	41	40	40	40	39	38	39	37

Note. P1 = Personalized ad of StoreA.com in position 1, P4 = Personalized ad of StoreA.com in position 4, NP1 = Non-personalized ad of StoreA.com in position 1, NP4 = Non-personalized ad of StoreA.com in position 4.

2.4.3 Results.

2.4.3.1 Validity and consistency checks.

A pretest using a scale adapted from Dabholkar (1994) tested the believability of the presented scenario, which confirmed that participants in both experiments perceived the shopping task to be realistic, easy to follow, and imaginable. In both experimental studies, participants rated believability of the given scenario as above the scale mean (*M*) (Study 1: M_{LAB1} = 5.56, *SD* = 1.38; Study 2 M_{LAB2} = 5.18, *SD* = 1.56). Results indicated that participants' selection of keywords from the pre-defined list did not make the situation unrealistic. Moreover, the data demonstrated that participants perceived that the ad fit their search queries better when the queries were included in StoreA.com's ad headline and URL ($M_{PERS,NO,LAB1}$

= 4.20 vs. $M_{PERS,YES,LAB1}$ = 5.45, $t(159) = -5.90$, $p < 0.001$; $M_{PERS,NO,LAB2}$ = 4.11 vs. $M_{PERS,YES,LAB2}$ = 4.70, $t(149) = -2.99$, $p = 0.003$).

2.4.3.2 Logistic regression.

The logistic regressions for the two competitive environments included two binary indicators for the experimental conditions (personalization vs. position); an interaction of both indicators; and age, gender, product involvement, and participants' native language as control variables. To test my hypotheses, I employed planned contrasts, because they allowed me to assess the effects of one experimental factor (e.g., personalization) for each level of the second experimental factor (high vs. low position). Table 2.3 displays the results of the logistic regressions. Column 1 depicts results for a non-personalized competitive environment and column 2 depicts results for a personalized competitive environment.

Table 2.3. Results of logistic regression with (1) non-personalized competitive ads and (2) personalized competitive ads

	Competitive ads			
	(1) Non-personalized		(2) Personalized	
	β (*SE*)	*p*-value	β (*SE*)	*p*-value
Intercept	-3.474 (5.102)	0.496	-0.138 (7.523)	0.857
Match (1 = yes)	3.163*** (0.647)	< 0.001	1.089 (0.884)	0.218
Position (1 = Position 1)	1.214† (0.650)	0.062	2.253** (0.817)	0.006
Match × Position	-0.774 (0.848)	0.361	-0.018 (1.009)	0.986
Age	0.008 (0.232)	0.973	0.003 (0.367)	0.994
Gender (1 = female)	-0.711 (0.435)	0.103	-0.390 (0.471)	0.407
Product involvement	0.277 (0.232)	0.231	-0.288 (0.217)	0.184
Native speaker (1 = yes)	0.213 (0.532)	0.689	-0.515 (0.698)	0.460
Akaike information criterion	173.074		159.657	
Log-Likelihood	-78.537		-71.829	
Deviance	157.074		143.657	

Note. † $p < 0.10$ * p < 0.05. ** p < 0.01. *** p < 0.001.

Column 1 of Table 2.3 shows that personalizing a focal firm's ad when its competitors do *not* personalize their search ads according to a consumer's search query significantly increases consumers' probability of clicking on the focal ad (β_{Match} 3.163, $p < 0.001$). As planned contrasts reveal, personalization of the focal ad increases click probabilities both for the top position ($\chi^2(1) = 18.876$, $p < 0.001$) and the lowest position ($\chi^2(1) = 23.885$, $p < 0.001$); this finding supports H_{1a}. In contrast, position has only a marginal effect on consumers' click probability ($\beta_{Position}$ 1.214, $p = 0.062$). This marginal effect is primarily driven by the condition in which the focal ad is non-personalized ($\chi^2(1) = 3.483$, $p = 0.062$), as indicated by planned contrasts. This finding supports H_{1b}. When the focal ad is personalized, planned contrasts show that the ad has no significant effect ($\chi^2(1) = 0.608$, $p = 0.418$). Furthermore, the interaction between ad personalization and ad positioning is not significant ($\beta_{Match \times Position}$ -0.774, $p = 0.361$).

In a personalized competitive environment, personalization of the focal ad has no significant effect on consumers' click probability (β_{Match} 1.089, $p = 0.218$). However, planned contrasts reveal that this finding holds only for ads in lower positions ($\chi^2(1) = 1.516$, $p = 0.218$). In higher positions, personalized ads increase consumer's click probabilities compared with non-personalized ads ($\chi^2(1) = 4.882$, $p = 0.027$), in support of H_{2a}. The results also reveal a positive main effect of the focal ad's position. In a personalized competitive environment, consumers are more likely to click on the focal ad if it is in a higher rather than lower position ($\beta_{Position}$ 2.253, $p = 0.006$). According to the planned contrasts, higher positions significantly increase click probabilities for personalized ($\chi^2(1) = 6.019$, $p = 0.028$) and non-personalized ($\chi^2(1) = 16.867$, $p < 0.001$) focal ads. Thus, H_{2b} receives partial support; the interaction effect between ad personalization and ad positioning is not significant ($\beta_{Match \times Position}$ -0.018, $p = 0.986$).

2.5 General Discussion

The findings of both laboratory experiments demonstrate that the importance of personalization and positioning effects in SEA is contingent on the competitive environment in which the ad of the focal firm is displayed. In line with consumer search theory (Dellaert & Häubl, 2012; Ratchford, 1982; Weitzman, 1979), as soon as competitors do not personalize their ads, personalized focal ads increase consumers' click probabilities, independent of the focal ad's position. In such situations, consumers search until they find an ad with high utility, which is best represented by matching the search ad to a consumer's search query (Klapdor et al., 2014; Rutz & Trusov, 2011). In situations in which none of the ads is personalized in this way, consumers are more likely to click on ads in higher rather than lower positions. Because consumers have learnt that search ads that better fit to their preferences are higher ranked in the search results, they perceive the ad in the first position to be the best among the worst (Parker & Schrift, 2011). However, as soon as competitors personalize their ads, ad personalization does not help the focal firm differentiate from its competitors.

This finding is in line with previous findings from Animesh et al. (2011), who show that a firm's price or quality USP loses its effectiveness when surrounding competitors use the same USP. I extend these results by showing that in such situations, an ad's position helps firms gain an advantage over competitors. Accordingly, personalized ads in higher positions are more effective than personalized ads in lower positions. However—contrary to my theoretical reasoning—positioning effects also are relevant when firms do *not* personalize their ads in a personalized competitive environment. A potential explanation for this finding is that in sequential searches, consumers are unduly sensitive to local influences (Häubl, Dellaert, & Donkers, 2009); they overweigh recently encountered alternatives over currently inspected alternatives. In my study, some consumers tended to use the non-personalized focal ad in the first position as a benchmark

against which they compared the personalized ad of the competitor below it. Even if the personalized ad generally have a higher utility than non-personalized ads, they still clicked on the non-personalized ad that they had encountered in the first place.

2.5.1 Theoretical contributions.

These findings make important contributions to SEA research. The results reveal that competitors' decisions to personalize their search ads represent an important boundary condition for personalization and positioning effects in SEA. Personalization causes an increase in click probabilities *only* if competitors do not personalize their ads or if personalized ads appear in the first position when competitors personalize. Positioning, in contrast, is most relevant when a firm's ad content does not differ from its competitors' ad content; in this case, it is the only criterion that differentiates a firm from its competitors. With this finding, I extend previous research on the influence of competition on ad effectiveness, which primarily investigated how the USPs of competitors' ads influence the effectiveness of a focal firm's USP (Animesh et al., 2011). Animesh et al. (2011) demonstrate that a firm's USP loses its effectiveness as soon as competitors use the same USP. Going beyond this finding, I show that ad positioning takes the role of ad personalization and allows firms to differentiate from competitors. Moreover, my results reveal that the personalization effect dominates the positioning effect. The latter becomes relevant only when a firm's personalized content offers no differentiation from its competitors. Thus, I elaborate on extant evidence on personalization effects (Rutz & Trusov, 2011) and positioning effects (Agarwal et al., 2011; Ghose & Yang, 2009; Narayanan & Kalyanam, 2015) that relates to each effect separately but does not investigate their potential interplay.

2.5.2 Managerial implications.

My findings also offer several valuable and actionable implications for practitioners. In general, firms should personalize their search ads even if they incur higher keyword management costs by creating unique ads for each keyword (Amaldoss et al., 2016). By personalizing their ads, firms increase the probability that consumers will click on their ads. In particular, in non-personalized competitive environments, consumers are more likely to click on personalized ads, independent of whether those ads appear in higher or lower positions in the search results. In the top positions of a personalized competitive environment, ad personalization becomes even more of an imperative for getting consumers' clicks. Only in the low positions of a personalized competitive environment should firms opt for non-personalized ads; because both personalized and non-personalized ads are equally effective in this environment, non-personalizing keyword ads reduces keyword management costs and is thus more efficient.

My results also demonstrate that firms should engage in costly bidding wars to win top positions (Agarwal et al., 2011) in *only two situations*: (1) when both firms and their competitors personalize their search ads, and (2) when firms have non-personalized ads and compete with these non-personalized ads against competitors' personalized ads.

2.5.3 Limitations and further research.

My results also offer potential avenues for further research. First, researchers could investigate how the personalization and positioning of paid search ads influence a consumer's tendency to click on paid or organic search results. Extant research has identified substantial interdependencies between these type of search results (Blake, Nosko, & Tadelis, 2015; Katona & Sarvary, 2009; Yang & Ghose, 2010). However, this research stream lacks findings on how concrete ad

design factors such as personalization or positioning influence consumers' decisions to click on paid or organic search results.

Second, additional studies could affirm the external validity of my findings through field experiments. Field experiments are important in online marketing research, because they allow causal inferences in the real world (Lambrecht & Tucker, 2015). To validate my results, a field experiment would need to manipulate an ad's personalization and positioning through bidding.

Third, research might contrast the relevance of personalization and positioning effects between stationary and mobile devices. Prior research has shown that consumers act differently on stationary and mobile devices (März, Schubach, & Schumann, 2017) and that, especially with regard to rank orderings, mobile devices strengthen positioning effects (Ghose, Goldfarb, & Han, 2013). Thus for example, researchers could investigate whether positioning effects regain importance on mobile devices when a firm personalizes its ads in a non-personalized competitive environment.

Fourth, in this study I employ either completely personalized or non-personalized competitor ads, so additional research might alter competitors' ads such that only some ads are personalized. Previous research on sequential search demonstrates that consumers are unduly sensitive to previously encountered alternatives and tend to compare them to the currently inspected alternative (Häubl et al., 2009); it would be worthwhile to test how consumers respond with click decisions when the previous or subsequent search ad is personalized or not personalized.

2.6 Conclusion

Prolific research has investigated the effectiveness of SEA and identified ad personalization and positioning as important drivers of search ad effectiveness. However, previous research lacks insights on how both strategies work together and

how they depend on competitors' personalization behavior. In this research, I demonstrate that personalizing ads helps firms differentiate from competitors when the competitors do not personalize their ads, and it becomes a necessity in personalized competitive environments. Ad positioning, in contrast, becomes important for firms only when their ads are no longer distinguishable from their competitors' ads. In this case, higher ad positions are more effective than lower ad positions. With my results, I make important contributions to SEA research and provide actionable implications for practitioners and further research.

2.8 References

Agarwal, A., Hosanagar, K., & Smith, M. D. (2011). Location, location, location: An analysis of profitability of position in online advertising markets. *Journal of Marketing Research*, *48*, 1057–1073. https://doi.org/10.1509/jmr.08.0468

Amaldoss, W., Jerath, K., & Sayedi, A. (2016). Keyword management costs and "Broad Match" in sponsored search advertising. *Marketing Science*, *35*, 259–274. https://doi.org/10.1287/mksc.2015.0919

Animesh, A., Viswanathan, S., & Agarwal, R. (2011). Competing "creatively" in sponsored search markets: The effect of rank, differentiation strategy, and competition on performance. *Information Systems Research*, *22*, 153–169. https://doi.org/10.1287/isre.1090.0254

Blake, T., Nosko, C., & Tadelis, S. (2015). Consumer heterogeneity and paid search effectiveness: A large-scale sield experiment. *Econometrica*, *83*, 155–174. https://doi.org/10.3982/ECTA12423

Broder, A. (2002). A taxonomy of web search. *ACM SIGIR Forum*, *36*, 3–10. https://doi.org/10.1145/792550.792552

Dabholkar, P. A. (1994). Incorporating choice into an attitudinal framework: Analyzing models of mental comparison processes. *Journal of Consumer Research*, *21*, 100–118. https://doi.org/10.1086/209385

Dellaert, B. G. C., & Häubl, G. (2012). Searching in choice mode: Consumer decision processes in product search with recommendations. *Journal of Marketing Research*, *49*, 277–288. https://doi.org/10.1509/jmr.09.0481

Dou, W., Lim, K. H., Su, C., Zhou, N., & Cui, N. (2010). Brand positioning strategy using search engine marketing. *MIS Quarterly*, *34*, 261–279. https://doi.org/10.2307/20721427

Ghose, A., Goldfarb, A., & Han, S. P. (2013). How is the mobile internet different? Search costs and local activities. *Information Systems Research*, *24*, 613–631. https://doi.org/10.1287/isre.1120.0453

Ghose, A., & Yang, S. (2009). An empirical analysis of search engine advertising: Sponsored search in electronic markets. *Management Science*, *55*, 1605–1622. https://doi.org/10.1287/mnsc.1090.1054

Google. (2018a). Get your ads above Google search results. Retrieved from https://support.google.com/google-ads/answer/1722087?hl=en

Google. (2018b). Keyword insertion. Retrieved from https://support.google.com/google-ads/answer/74992?hl=en

Haans, H., Raassens, N., & van Hout, R. (2013). Search engine advertisements: The impact of advertising statements on click-through and conversion rates. *Marketing Letters*, *24*, 151–163. https://doi.org/10.1007/s11002-013-9226-5

Häubl, G., Dellaert, B. G. C., & Donkers, B. (2009). Tunnel vision: Local behavioral influences on consumer decisions in product search. *Marketing Science*, *29*, 438–455. https://doi.org/10.1287/mksc.1090.0525

Jeziorski, P., & Moorthy, S. (2018). Advertiser prominence effects in search advertising. *Management Science*, *64*, 1365–1383. https://doi.org/10.1287/mnsc.2016.2677

Katona, Z., & Sarvary, M. (2009). The race for sponsored links: bidding patterns for search advertising. *Marketing Science*, *29*, 199–215. https://doi.org/10.1287/mksc.1090.0517

Klapdor, S., Anderl, E. M., Wangenheim, F. von, & Schumann, J. H. (2014). Finding the right words: The influence of keyword characteristics on performance of paid search campaigns. *Journal of Interactive Marketing*, *28*, 285–301. https://doi.org/10.1016/j.intmar.2014.07.001

Lambrecht, A., & Tucker, C. (2015). Field experiments in marketing. Retrieved from http://ssrn.com/abstract=2630209

März, A., Schubach, S., & Schumann, J. H. (2017). “Why would I read a mobile review?” Device compatibility perceptions and effects on perceived helpfulness. *Psychology & Marketing*, *34*, 119–137. https://doi.org/10.1002/mar.20979

Narayanan, S., & Kalyanam, K. (2015). Position effects in search advertising and their moderators: A regression discontinuity approach. *Marketing Science*, *34*, 388–407. https://doi.org/10.1287/mksc.2014.0893

Parker, J. R., & Schrift, R. Y. (2011). Rejectable choice sets: How seemingly irrelevant no-choice options affect consumer decision processes. *Journal of Marketing Research*, *48*, 840–854. https://doi.org/10.1509/jmkr.48.5.840

PwC. (2017). IAB internet advertising revenue report: 2017 full year results. Retrieved from https://www.iab.com/wp-content/uploads/2018/05/IAB-2017-Full-Year-Internet-Advertising-Revenue-Report.REV2_.pdf

Rangaswamy, A., Giles, C. L., & Seres, S. (2009). A strategic perspective on search engines: Thought candies for practitioners and researchers. *Journal of Interactive Marketing*, *23*, 49–60. https://doi.org/10.1016/j.intmar.2008.10.006

Ratchford, B. T. (1982). Cost-benefit models for explaining consumer choice and information seeking behavior. *Management Science*, *28*, 197–212. https://doi.org/10.1287/mnsc.28.2.197

Roehm, M., & Roehm, H. (2011). The influence of redemption time frame on responses to incentives. *Journal of the Academy of Marketing Science*, *39*, 363–375. https://doi.org/10.1007/s11747-010-0201-x

Rutz, O. J., & Bucklin, R. E. (2011). From generic to branded: A model of spillover in paid search advertising. *Journal of Marketing Research*, *48*, 87–102. https://doi.org/10.1509/jmkr.48.1.87

Rutz, O. J., Bucklin, R. E., & Sonnier, G. P. (2012). A latent instrumental variables approach to modeling keyword conversion in paid search advertising. *Journal of Marketing Research*, *49*, 306–319. https://doi.org/10.1509/jmr.10.0354

Rutz, O. J., & Trusov, M. (2011). Zooming in on paid search ads—A consumer-level model calibrated on aggregated data. *Marketing Science*, *30*, 789–800. https://doi.org/10.1287/mksc.1110.0647

Statista. (2017). Digital advertising report 2017–Search advertising: Statista digital market outlook –Segment report. Retrieved from https://de.statista.com/statistik/studie/id/38319/dokument/digital-advertising-report-search-advertising/

Weitzman, M. L. (1979). Optimal search for the best alternative. *Econometrica*, *47*, 641–654. https://doi.org/10.2307/1910412

Yang, S., & Ghose, A. (2010). Analyzing the relationship between organic and sponsored search advertising: Positive, negative, or zero interdependence? *Marketing Science*, *29*, 602–623. https://doi.org/10.1287/mksc.1090.0552

Zaichkowsky, J. L. (1994). The personal involvement inventory: Reduction, revision, and application to advertising. *Journal of Advertising*, *23*, 59–70. https://doi.org/10.1080/00913367.1943.10673459

3. Study 2: How Online Shopping Behavior Informs Positioning Strategies in Search Engine Advertising

Sebastian Schubach, Jan H. Schumann, Alexander Bleier

Will be submitted to *Marketing Science* (VHB Ranking: A+)

Search engine advertising (SEA), the most important channel in online advertising, targets consumers at the moment they actively search for information. Recent technological advances now allow advertising firms to retarget consumers on search engines, by integrating information about their search queries with tracked information about their previous online shopping behavior. Yet insights into how the effectiveness of ad positions, the main lever in SEA, varies with consumers' previous online shopping behavior are still missing. Based on a field experiment and 18 weeks of observational data, this research finds that consumers in early stages of the buying process are more susceptible to the influence of ad positions (as per their click and conversion behavior) than consumers in later stages. However, conditional on click, consumers in later stages are more likely to convert. Firms thus need to balance the effects of ad positions and consumers' stages in the buying process in order to maximize overall clicks and conversions. The results outline the potential of strategically adjusting ad positions to consumers' previous online shopping behavior and indicate fruitful opportunities for further research in a new domain we label "SEA retargeting."

3.1 Introduction

Search engine advertising (SEA) constitutes the most critical online advertising channel, accounting for almost half of worldwide online advertising spending, an $88 billion industry. SEA is effective, because it allows firms to strategically target consumers with ads in the moment they are actively searching for information and might thus be especially susceptible to marketing communications (Shankar & Malthouse, 2007). In particular, in SEA, firms bid on keywords that consumers might use in their search queries. As soon as consumers include those keywords in their queries, the search engine runs an auction based on firms' keyword bids to determine whether and in which position the firm's ad is shown on the search engine's result page. A new feature on Google called Remarketing Lists for Search Ads (RLSA) now enables advertising firms to combine information about consumers' current searches with insights about their previous online shopping behavior (Google, 2018a). In this way, RLSA challenges firms' long-standing mere focus on search queries as their main source of information on consumers' preferences and joins SEA with retargeting technologies (Lambrecht & Tucker, 2013). RLSA allows firms to identify previous visitors and adapt their advertising according to those visitors' search queries and previous shopping behavior. Marketers are increasingly using RLSA, also because information about consumers' online shopping behavior is private to them and thus offers a competitive advantage. Since end of 2016, ad clicks on Google from RLSA more than tripled, from 10% to 31% (Merkle, 2018), making RLSA a fast growing market.

Yet, despite its popularity, how to strategically leverage RLSA in order to display ads in the right positions for increased click and conversion rates from previous visitors is still unclear. In line with Google's recommendations, most firms currently aim to display ads in higher positions (i.e., higher on Google's search results page) for consumers who have advanced further in the buying process by placing higher bids on keywords from them (Google, 2016). Google's rationale

behind this recommendation is that consumers in later stages of the buying process are more valuable to a firm, because they have a higher conversion potential (Bucklin & Sismeiro, 2003; Moriguchi, Xiong, & Luo, 2016). However, no empirical studies have so far investigated whether consumers in later compared to earlier stages of their buying process are indeed more likely to click and convert from ads in higher positions, an implicit assumption of this positioning strategy. So far, we only know that, in general, the position of an ad on the search results page drives consumers' click and conversion behavior (Narayanan & Kalyanam, 2015), but not how consumers in different stages in their buying process respond to ad positions. This investigation is important as the online shopping literature affirms that the effectiveness of subsequent online marketing activities depends on a consumer's stage in the buying process (Bleier & Eisenbeiss, 2015). Knowing how ad positions relate to ad effectiveness for consumers at different stages of the buying process would inform firms in how to design effective and efficient positioning strategies in SEA. Thus, in the current study, we use two field studies conducted in collaboration with a German search agency to investigate how a consumer's stage in the buying process influences his or her response to ad positions in SEA.

To gain a first understanding of how a consumer's stage in the buying process influences the effectiveness of different ad positions, we employ a field experiment that tests Google's recommended and widely adopted positioning strategy to increase positions more for consumers in later compared to early stages of the buying process. To modify ad positions, we manipulated keyword bids for an international multibrand fashion retailer on Google and increased existing bids more for consumers in later than in earlier stages. Our results show that higher ad positions lead to higher click-through rates for consumers in both early and later stages. Yet, for conversion rates, we find that while higher positions leave rates unchanged for consumers in early stages, they actually cause a substantial *drop* in conversion rates for consumers in later stages, which calls the merit of this strategy

into question. Since the tested bidding scheme did not increase ad positions equally across all stages of the buying process, we cannot directly compare the effect of a position change between different stages. Thus, we subsequently analyzed the differences in consumers' responses to ad positions dependent on their stage in the buying process more deeply with 18 weeks of observational data, in which the partnering firm's positioning strategy was not conditioned on consumers' stages in the buying process. In particular, we use a hierarchical Bayesian model to assess how consumers in different stages of the buying process respond to ad positions in their click and conversion behavior. Our results show, that consumers early in the process are more susceptible to higher ad positions than consumers later in the process, for both click and conversion measures. Consumers later in the process also are more likely to click on ads in higher positions, but less likely to convert after clicking on ads in higher compared to lower positions. Accordingly, firms might benefit from a strategy that positions search ads higher for consumers in early rather than late stages of their buying process. However, our analyses further reveal that conditional on click, consumers in later stages of the buying process are more likely to convert. With a positioning strategy, where ads appear in higher positions for consumers early in their buying process, firms would therefore risk to forgo valuable consumers in later stages with a higher purchase likelihood. Thus, based on our results, firms need to balance the effects of ad positions and consumers' stages in the buying process.

3.2 Related Literature and Contributions

Extant research on position effects has shown that click probabilities are higher for search ads in higher positions on the search results page (Agarwal, Hosanagar, & Smith, 2011; Ghose & Yang, 2009). However, position effects also depend on whether consumers submit generic, brand-related, or firm-related keywords (Ghose & Yang, 2009; Narayanan & Kalyanam, 2015), the firm's size

(Jeziorski & Moorthy, 2018; Narayanan & Kalyanam, 2015), the firm's focus on quality or price in its ads (Animesh, Viswanathan, & Agarwal, 2011), the weekday, and consumers' prior experiences with a given keyword (Narayanan & Kalyanam, 2015). To which extent ad positions matter for consumers' purchase decisions remains ambiguous. Ghose and Yang (2009) show that position effects are similar for both click and conversion rates, such that ads in higher positions yield higher rates, but Agarwal et al. (2011) find that lower positions prompt higher conversion rates, especially if the ads relate to specific search queries. Narayanan and Kalyanam (2015) provide evidence that ad position has negligible effects on conversion rates. We contribute to this research by investigating a consumer's stage in the buying process as a new boundary condition for position effects. Whereas previous research did not differentiate between consumers that had or had not visited the firm's online store previously, we explicitly include this information and investigate how it affects position effects.

Understanding the impact of consumers' online shopping behavior on the effectiveness of different ad positions is important, as research in this area has shown that consumers respond differently to marketing activities depending on whether they previously visited an online store or not. This research, the second stream we contribute to, specifically investigates consumers' click- and conversion-behavior in response to display ads and emails that are personalized based on information from consumers' most recent visit to the firm's online store. Studies show that such retargeting activities can induce consumers to return to the firm's online store and increase sales (Johnson, Lewis, & Nubbemeyer, 2017; Sahni, Narayanan, & Kalyanam, 2018), but their effectiveness depends on a consumer's stage in the buying process. For consumers' click decision, Bleier and Eisenbeiss (2015) as well as Sahni et al. (2018) demonstrate that the incremental value of retargeting is greater for consumers in early stages of the buying process. For consumers' conversion decision, the opposite is true. In this way, Lambrecht and

Tucker (2013) and Moriguchi et al. (2016) provide evidence that consumers in later stages exhibit higher purchase probabilities in response to retargeting efforts. In our research, we acknowledge the relationship between these two performance metrics and jointly model consumers' click and conversion decision, allowing for potential correlations between both decisions. Moreover, we move beyond personalized display and email contexts to investigate the impact that the stage in the buying process has on SEA position effects. We thereby recognize that the SEA context differs fundamentally from other types of advertising, because ads appear in response to a consumer's active search for information. In contrast, in most other advertising contexts, it is the advertiser who pushes ads to consumers (Shankar & Malthouse, 2007). Practitioners should use our findings to carefully monitor and adjust their positioning strategies instead of blindly relying on Google's recommendation to primarily focus on consumers in later stages.

3.3 Technical Background

In SEA, firms place bids on keywords that consumers are likely to use in their search queries. For each search query submitted by a consumer, Google runs a second-price auction in which firms bid on those keywords. The ad rank—which multiplies the keyword's bid with its quality score—determines the outcome of the auction, that is, the position in which firms' ads will be shown to consumers. High ad ranks mean appearing in higher positions on the results page, low ad ranks mean appearing in lower positions. In the end, firms have to pay for each click on their ads.

The recent introduction of RLSA allows firms to combine information revealed in the search query with tracked information about consumers' prior online shopping behavior in the firm's online store. This information offers a competitive advantage to firms, as it is private information to them and competitors do not have access to it. To collect information about consumers' prior online shopping behavior

firms must integrate a remarketing pixel into their online store. Each time a consumer visits a new page in that store, the pixel is loaded, and the online store places a cookie on the consumer's device with information about which pages he or she has visited. Firms can thus develop unique consumer profiles. Moreover, they can segment consumers' online shopping behavior according to pre-defined criteria, using remarketing lists. With the help of a percentage multiplier, firms subsequently adjust their existing bids for these segments by some particular percentage value to alter the ads' positions. As soon as a consumer exhibits one of the pre-defined behaviors in the online store, Google assigns this person to the corresponding segment. With cookies, Google identifies in which segment each consumer is in at the moment he or she submits a search query and applies the specific bid value for keywords of this segment.

3.4 Pilot Study: Field Experiment to Test Current Industry Practice

In the pilot study, we partnered with a German search advertising agency and an international multibrand fashion retailer. The aim of this study was to systematically test Google's recommended and widely adopted positioning strategy that aims to display ads in more prominent positions for consumers in later stages of their buying process.

3.4.1 Study setup.

3.4.1.1 Technical setup.

For the test, we ran a field experiment on Google's search engine in one of the retailer's national markets in February 2016. Prior to the experiment, the retailer implemented the required remarketing tag on each page of its online store to identify consumers who visited the online store prior to submitting a search query (previous visitors). We defined four primary behaviors as proxies of a consumer's stage in the buying process and created a segment for each stage. If consumers exhibited one

of these behaviors, Google assigned them to the corresponding segment, as follows:

- *Site visitors* visited either the top-level page of the online store or browsed one or more category-level pages.
- *Product viewers* looked at one or more specific product pages.
- *Cart abandoners* visited the shopping cart page.
- *Previous buyers* purchased one or more products.

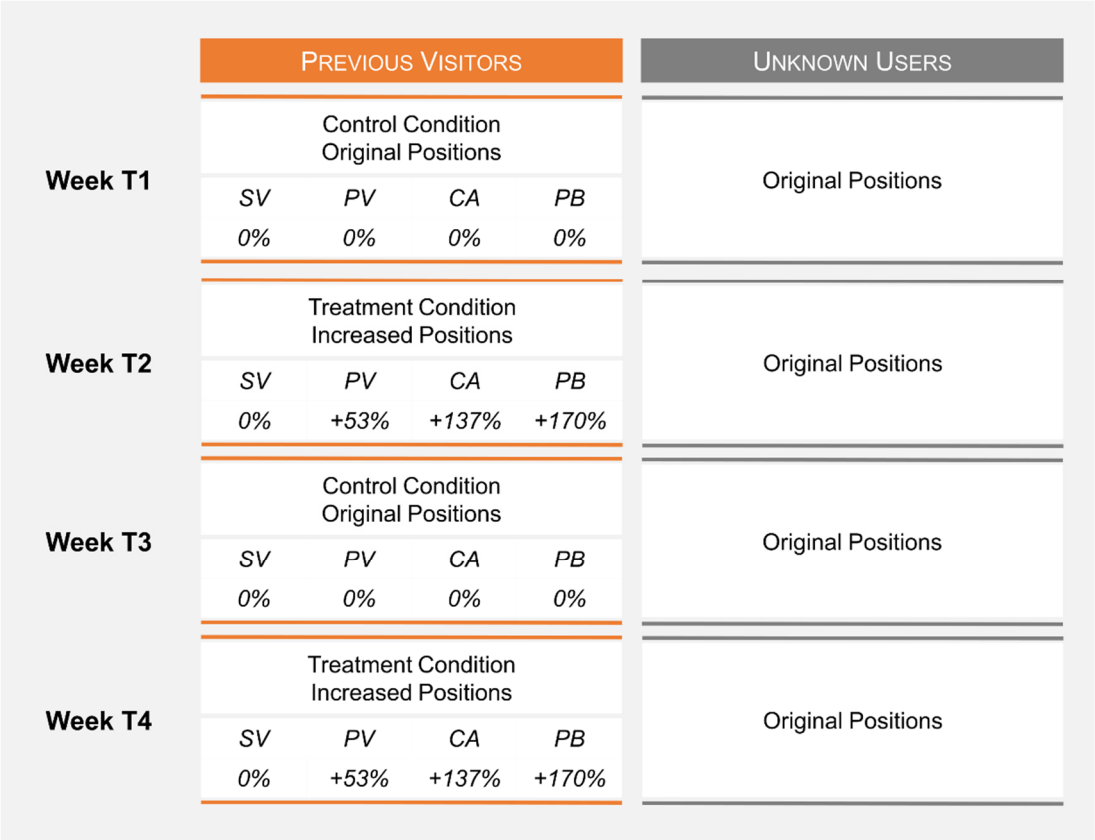
Consumers who exhibited more than one of these behaviors were assigned to the segment that features the latest stage they fit. For example, we define consumers that visited top-level pages and looked at product pages as product viewers only. For each segment, the retailer could aim for a change in the ads' positions by changing its keyword bids according to the percentage multiplier.

3.4.1.2 Experimental manipulation.

Figure 3.1 illustrates the design of our experiment. In the treatment conditions, relative to the retailer's current practices, we increased keyword bids more for consumers in later phases than for consumers in early phases of the buying process to increase positions more for those consumers in later stages. We use a 0% percentage multiplier for site visitors, a +53% multiplier for product viewers, a +137% multiplier for cart abandoners, and a +170% multiplier for previous buyers. Thus, an existing bid of $1 for a particular keyword would remain $1 for site visitors but increase to $1.53 for product viewers, $2.37 for cart abandoners, and $2.70 for previous buyers. These specific percentage values are in line with Google's proposed strategy, as well as the agency's agreements with the partnering retailer. In the control condition, the bids remained at their existing level for all consumers, so that ads should remain in the original position.

As a randomized assignment of consumers to the treatment and the control condition was technically not feasible, we decided to rotate treatments across time, following Yang and Ghose (2010). We assigned all previous visitors to the control condition in weeks 1 and 3 and to the treatment condition in weeks 2 and 4. The time period of 7 days reduces the possibility that consumers would be in both the treatment and control condition, as typical purchase cycles in the online fashion industry take place within one week (KPMG, 2017). Thus, our setup minimizes cross-over effects that potentially reduce the reliability of the treatment effect (Lambrecht & Tucker, 2013). To control for variation in the outcomes due to the specific week the experiment took place, we used consumers who had not visited the retailer's online store previously (unknown users) as baseline condition. For those consumers positions remained at the original level throughout the entire experimental period. As such, we are able to separate out the variation caused by the treatment from that caused by week-specific effects.

Figure 3.1. Experimental design of field experiment



Note. SV = site visitors, PV = product viewers, CA = cart abandoners, PB: previous buyers, previous visitors = consumers that were in the retailer's online store, unknown users = consumers that had not visited the retailer's online store. Percentage values represent percentage multipliers.

3.4.2 Data.

The search advertising agency provided data about each keyword's impressions, clicks, conversions, costs, and average position for each defined consumer segment in the treatment and control condition. We also obtained data about keywords searched by unknown users, our baseline condition. We only included keywords searched by both previous visitors and unknown users for our analysis. In total, our data comprises 4,882 keywords.

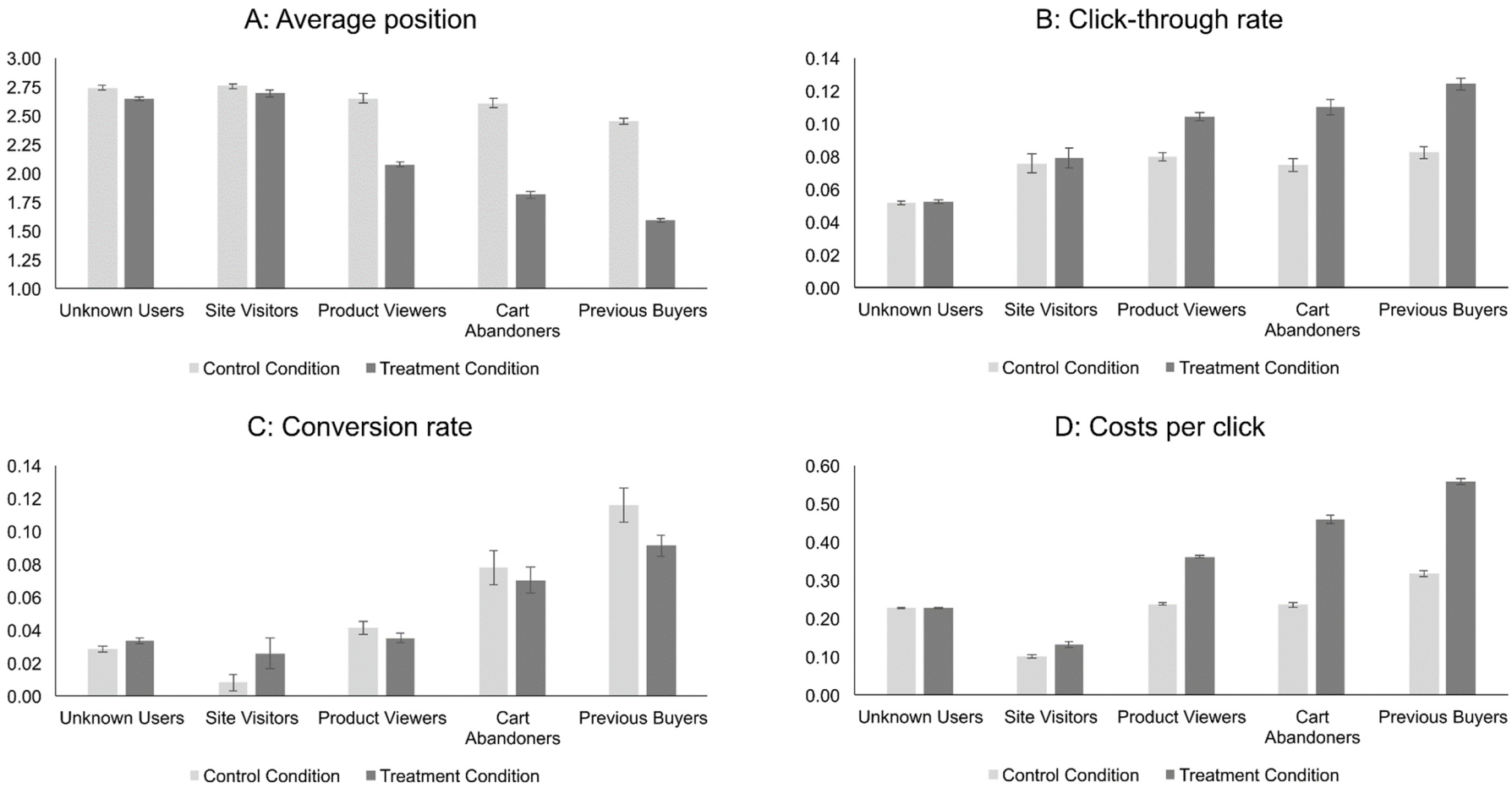
We employed a difference-in-differences approach to investigate whether being in one of the previous visitor segments and in the treatment condition adds additional variation to the variation caused by the visitor type (previous visitor vs. unknown user) and the experimental condition (treatment vs. control condition). Thus, for each segment, we assess differences in the outcome measures between the segments and unknown users in the treatment and in the control condition. The

difference in these differences then captures the treatment effect of the positioning strategy. We used consumers' click and conversion rate as outcome measures to determine the effectiveness of increased ad positions, and costs per click to assess the efficiency.

3.4.3 Results.

Figure 3.2 and Table 3.1 display the results of our analysis. As a manipulation check, we find that, as intended, ad positions remain the same for site visitors (0.338, $p = 0.567$), but increase significantly for product viewers (-0.476, $p < 0.001$), cart abandoners (-0.699, $p < 0.001$) and previous buyers (-0.770, $p < 0.001$), as shown by the difference in differences in average position between the treatment and control condition across each segment (panel A). Similarly, panel B shows that click-through rates increase significantly for product viewers (0.024, $p < 0.001$), cart abandoners (0.035, $p < 0.001$) and previous buyers (0.041, $p < 0.001$) as the difference to unknown users is for each segment significantly higher in the treatment condition (column (1)) than in the control condition (column (2)). The increase in click-through rates is highest for previous buyers for whom ad positions increased the most. As positions did not increase for site visitors, we find no change in click-through rates for them (0.003, $p = 0.706$). Panel C further reveals that the increase in ad positions led to a smaller difference in conversion rates in the treatment condition than in the control condition for previous buyers (-0.030, $p < 0.001$), suggesting that the manipulation caused a drop in conversion rates. Moreover, increasing ad positions also resulted in higher costs per click, especially for cart abandoners (0.221, $p < 0.001$) and previous buyers (0.238, $p < 0.001$) as indicated by the difference in differences in panel D.

Figure 3.2. Difference in average position (panel A), click-through rate (panel B), conversion rate (panel C), and costs per click (panel D) by visitor type and experimental condition



Note. Error bars represent standard errors.

Table 3.1. Differences in average position, click-through rates, conversion rates and costs per click between treatment and control conditions by visitor type

	Experimental condition					
	(1) Treatment		(2) Control			
Previous visitor segment	Difference to unknown users	*F*-Value	Difference to unknown users	*F*-Value	DID: (1)–(2)	*F*-Value
A: Average position						
Site visitors	0.0473	1.24	0.0135	0.11	0.3380	0.33
Product viewers	-0.5698***	421.98	-0.0940***	11.42	-0.4758***	146.75
Cart abandoners	-0.8325***	628.25	-0.1333***	15.33	-0.6992***	216.07
Previous buyers	-1.0574***	1232.71	-0.2876***	86.87	-0.7698***	318.90
B: Click-through rate						
Site visitors	0.0269***	25.42	0.0241***	21.95	0.0028	0.14
Product viewers	0.0519***	221.72	0.0283***	65.74	0.0235***	22.80
Cart abandoners	0.0577***	191.53	0.0232***	29.57	0.0345***	33.31
Previous buyers	0.0718***	360.93	0.0307***	63.02	0.0411***	57.63
C: Conversion rate						
Site visitors	-0.0078	0.59	-0.0200*	3.99	0.0122	0.73
Product viewers	0.0016	0.13	0.0131**	7.38	-0.0115	3.07
Cart abandoners	0.0368***	33.58	0.0495***	41.99	-0.0127	1.64
Previous buyers	0.0578***	125.04	0.0876***	201.95	-0.0298***	13.73
D: Costs per click						
Site visitors	-0.0961***	93.88	-0.1255***	165.54	0.0293*	4.45
Product viewers	0.1332***	947.48	0.0166*	6.18	0.1215***	363.21
Cart abandoners	0.2308***	1391.92	0.0100	1.82	0.2207***	519.98
Previous buyers	0.3292***	4276.60	0.0908***	228.69	0.2384***	925.99

Note. DID = Difference-in-differences. Significances calculated with analyses of variance.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.4.4 Discussion.

The results of our pilot study provide first evidence that consumers respond differently to ad positions in their click and conversion decision dependent on their particular stage in the buying process. In particular, ads in more prominent positions have a stronger influence on consumers' click decisions in later than in earlier stages of the buying process. Yet, consumers in later stages are less likely to convert after clicking on ads from higher compared to lower positions while the conversion decision remains unaffected by an ad's position for consumers in early stages. Thus, our pilot study yields first insights that consumers' responses to ad positions hinge on their stage in the buying process. However, it does not allow us to directly compare click and conversion rates between different stages of the

buying process, as the increase of ad positions differed between the stages, as per our design. In the main study, we therefore use observational data with unchanged bid amounts and, thus, positions, to analyze differences in click and conversion responses to ad positions between consumers in different stages of their buying process.

3.5 Observational Study: Consumers' Responses to Ad Positions

3.5.1 Study setup and data.

After the field experiment, the collaborating search agency continued to collect data from consumers in the four segments, but did not increase bids to alter the ads' positions for those segments. We obtained keyword data for 18 weeks (April–July 2016) related to the number of impressions, clicks, conversions, and average position for a given keyword in a given consumer segment. These data also allowed to control for the device on which ads where shown (i.e., desktop PC, tablet, or smartphone). We focused on the top 20% of keywords in terms of average impressions; these 617 keywords account for almost 90% of all impressions, clicks, and conversions and yielded 73,204 usable observations. As the overview in Table 3.2 shows, on average, keyword ads were most often displayed to product viewers (M = 21.44, SD = 39.71), followed by previous buyers (M = 11.93, SD = 21.57) and site visitors (M = 8.68, SD = 18.71). Keyword ads shown to previous buyers have the highest click-through probabilities (M = 0.10, SD = 0.18), and the highest conversion probabilities (M = 0.13, SD = 0.28). Next, we model the influence of an ad's position on click and conversion probabilities for each of the four consumer segments and determine how those position effects vary between consumer segments. To do so, we interact the ad's position and the segment a consumer is in.

3.5.2 Model.

We use a hierarchical Bayesian framework to estimate consumers' clicks and conversions for a given keyword i in a consumer segment c on a device d in a week t (Ghose & Yang, 2009). The likelihood to simultaneously observe a particular combination of clicks and conversions given a number of impressions is defined by:

$$f(n_{icdt}, m_{icdt}, p_{icdt}, q_{icdt}) = \frac{N_{icdt}!(p_{icdt}q_{icdt})^{m_{icdt}}[p_{icdt}(1-q_{icdt})]^{n_{icdt}-m_{icdt}}(1-p_{icdt})^{N_{icdt}-n_{icdt}}}{m_{icdt}!(n_{icdt}-m_{icdt})!(N_{icdt}-n_{icdt})} \quad (1)$$

where N_{icdt} is the number of impressions, n_{icdt} is the number of clicks, m_{icdt} is the number of conversions, p_{icdt} is the click probability, and q_{icdt} is the conversion probability. As our model estimates consumers' click and conversion probabilities, in the following, we outline our parameterization of both probabilities.

3.5.2.1 Parameterization of click probability.

We parameterize the click probability p_{icdt} of keyword i in segment c on device d in a given week t with a logistic parameterization:

$$p_{icdt} = \frac{\exp(\alpha' X_{icdt})}{1+\exp(\alpha' X_{icdt})} \quad (2)$$

The click probability depends on the vector of covariates X_{icdt}. In line with our research question, we are interested in the influence of a keyword's position, the specific consumer segment to which the keyword ad was delivered, and the interaction of the ad's position and the segment. Thus, we specify $\alpha' X_{icdt}$ as follows:

$$\alpha' X_{icdt} = \alpha_{i0} + \alpha_1' SEGMENT_{icdt} + \alpha_2 POS_{icdt} + \alpha_3' SEGMENT_{icdt} POS_{icdt} + \alpha_4 QS_{icdt} + \alpha_5 COMP_{icdt} + \alpha_6 BRAND_{icdt} + \alpha_7 CAT_{icdt} + \alpha_8' DEVICE_{icdt} + \alpha_9' TIME_{icdt} \quad (3)$$

where $SEGMENT_{icdt}$ is a vector of dummy-coded variables that captures a consumer's stage in the buying process, and POS_{icdt} is the ad's position. We included the keyword's quality score QS_{icdt} and the level of competition for a given

keyword as control variables (Agarwal et al., 2011; Rutz & Trusov, 2011). The quality score reflects the quality of a keyword according to its previous performance or the quality of the corresponding landing page, for example. We assess the level of competition with Google's Keyword Planner (Google, 2018b), which links the number of competitors bidding on a keyword i to the number of competitors that bid on any keyword in a predefined geographic region. The dummy variables $BRAND_{icdt}$ and CAT_{icdt} capture content and linguistic characteristics of the keyword (Ghose & Yang, 2009; Narayanan & Kalyanam, 2015), namely, whether it contains brand information (= 1) or not (= 0), and whether it contains product category information (= 1) or not (= 0). The vector of dummy-coded variables $DEVICE_{icdt}$ controls for device-specific effects, because consumers behave differently on stationary and mobile devices (Ghose, Goldfarb, & Han, 2013). The vector includes dummies for whether consumers searched for a keyword on a tablet or a mobile phone; desktop served as reference category. The vector $TIME_{icdt}$ captures time-specific effects in the 18 weeks observation period. It includes 17 dummy-coded variables. The first week serves as reference week. In line with previous studies (Agarwal et al., 2011; Ghose & Yang, 2009), we additionally introduce a random intercept α_{i0} to capture heterogeneity in keywords. The intercepts are randomly distributed around the population mean, as follows:

$$\alpha_{i0} = \overline{\alpha_0} + \varepsilon_{i0}^{\alpha} \tag{4}$$

3.5.2.2 Parameterization of conversion probability.

The logit function to parameterize the keyword's conversion probability is similar to the specification for the keyword's click probability:

$$q_{icdt} = \frac{\exp(\beta' X_{icdt})}{1+\exp(\beta' X_{icdt})} \tag{5}$$

We estimate the conversion probability for the consumer segment ($SEGMENT_{icdt}$) for which the ad is delivered, the ad's position (POS_{icdt}), and their interaction. Furthermore, we use the keyword's quality score (QS_{icdt}), keyword characteristics ($BRAND_{icdt}$ and CAT_{icdt}), the device ($DEVICE_{icdt}$) and time-dummies ($TIME_{icdt}$) as control variables:

$$\beta' X_{icdt} = \beta_{i0} + \beta_1' SEGMENT_{icdt} + \beta_2 POS_{icdt} + \beta_3' SEGMENT_{icdt} POS_{icdt} + \beta_4 QS_{icdt} + \beta_5 BRAND_{icdt} + \beta_6 CAT_{icdt} + \beta_7' DEVICE_{icdt} + \beta_8' TIME_{icdt} \quad (6)$$

As for the parameterization of the click probability, we introduce a random intercept β_{i0}, that is distributed according to:

$$\beta_{i0} = \overline{\beta_0} + \varepsilon_{i0}^{\beta} \quad (7)$$

An ad's position is the outcome of an auction that the search engine runs and that firms can influence with their bids. This determination of the ad's position raises questions about endogeneity as unobserved factors could influence this position as well as click and conversion probabilities (Agarwal et al., 2011; Ghose & Yang, 2009). To address this potential endogeneity, we start by explicitly modelling the search engine's auction. The auction determines the position based on the firm's maximum bid ($MAXCPC_{icdt}$) and the keyword's quality score QS_{icdt} (Agarwal et al., 2011; Ghose & Yang, 2009). Furthermore, we assume that the device ($DEVICE_{icdt}$) and time-specific effects ($TIME_{icdt}$) influence the outcomes. In line with Agarwal et al. (2011), we log-transform the ad position, the maximum bid, and the quality score, such that

$$\ln(POS_{icdt}) = \gamma_{i0} + \gamma_1 \ln(MAXCPC_{icdt}) + \gamma_2 \ln(QS_{icdt}) + \gamma_3' DEVICE_{icdt} + \gamma_4' TIME_{icdt} + \varepsilon_{POS,icdt} \quad (8)$$

Similar to the click- and conversion probabilities, we model a random intercept, distributed around the population mean:

$$\gamma_{i0} = \overline{\gamma_0} + \varepsilon_{i0}^{\gamma} \quad (9)$$

If unobserved factors influence the outcome of the auction and the keyword's click or conversion probabilities, equations (3), (6), and (8) correlate (Agarwal et al., 2011; Ghose & Yang, 2009). Accordingly, we explicitly correlate the keyword-specific error terms $\varepsilon_{i0}^{\alpha}$, ε_{i0}^{β}, and $\varepsilon_{i0}^{\gamma}$ from the random intercepts in these equations, with the rationale that most of the SEA decisions that firms and search engines make are keyword-based. The influence of unobserved factors thus should be similar within each keyword. We assume the keyword-specific error terms to be distributed multivariate normal with mean zero and an unstructured variance-covariance matrix.

$$\begin{bmatrix} \varepsilon_{i0}^{\alpha} \\ \varepsilon_{i0}^{\beta} \\ \varepsilon_{i0}^{\gamma} \end{bmatrix} \sim MVN \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \Omega_{11} & \Omega_{12} & \Omega_{13} \\ \Omega_{21} & \Omega_{22} & \Omega_{23} \\ \Omega_{31} & \Omega_{13} & \Omega_{33} \end{bmatrix} \right) \tag{10}$$

3.5.3 Validity of results.

Biases that might arise due to our research design could limit the comparability of the four consumer segments. For example, Google might use information about a consumer's buying process stage for targeting purposes, so that ads would appear in different positions for different consumer stages. However, Table 3.2 indicates that the ad position varies only little across the four consumer segments, with the possible exception of site visitors (M_{SV} = 2.93, SD_{SV} = 1.37). This difference likely reflects the high share of keywords that consumers submit through their mobile phones (84%); search engines allow firms to target and bid for mobile phone users specifically. Thus, the difference in position likely arises through device targeting rather than targeting a specific consumer segment. Another potential bias could arise if consumers early in their buying process use different keywords than those that have advanced further; for example, the use of branded or product category-related keywords could signal consumers' stages in the buying process (Agarwal et al., 2011; Narayanan & Kalyanam, 2015; Rutz & Bucklin, 2011).

However, in our data, the share of branded keywords is stable over all four segments (0.43 to 0.46), as is the share of keywords with information about product categories (0.69 to 0.71). As such, the four consumer segments seem comparable, and our estimates should be reliable and valid.

Table 3.2. Keyword summary statistics per week and per device by stage in the buying process

	Consumer segment							
	Site visitors		Product viewers		Cart abandoners		Previous buyers	
	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*
Impressions	8.68	18.71	21.44	39.71	5.59	8.72	11.93	21.57
Position	2.93	1.37	2.68	1.21	2.51	1.29	2.51	1.22
Click-through rate	0.07	0.17	0.09	0.13	0.09	0.20	0.10	0.18
Conversion rate	0.01	0.11	0.05	0.16	0.10	0.27	0.13	0.28
Costs per click	0.15	0.12	0.33	0.19	0.33	0.20	0.38	0.20
Quality score	8.04	1.43	7.91	1.48	7.99	1.47	7.95	1.47
Competition	0.75	0.31	0.74	0.32	0.74	0.32	0.74	0.32
Max. CPC	0.35	0.13	0.34	0.12	0.35	0.12	0.35	0.12
Brand	0.43	0.50	0.46	0.50	0.45	0.50	0.46	0.50
Category	0.71	0.45	0.69	0.46	0.70	0.46	0.69	0.46
PC	0.11	0.31	0.38	0.48	0.50	0.50	0.50	0.50
Tablet	0.05	0.22	0.32	0.47	0.18	0.38	0.28	0.45
Mobile	0.84	0.37	0.31	0.46	0.32	0.47	0.22	0.41
Observations	8,989		27,351		16,908		19,956	

3.5.4 Results.

We estimated our model with the Hamiltonian Monte Carlo algorithm and a No-U-Turn-Sampler using rstan. We use weakly informative priors to regularize extreme inferences and guarantee the stability of our estimates (Gelman, Jakulin, Pittau, & Su, 2008), then estimate four chains in parallel with 2,500 draws for burn-in and 2,500 draws for sampling. We discarded the burn-in draws and only used the sample draws for the posteriors. The scale reduction factors of all posterior estimates are near 1 and below the critical value of 1.1 (Brooks & Gelman, 1998; Gelman & Rubin, 1992), indicating model convergence. To compare estimates, we estimated the model four times, shifting the reference category for $SEGMENT_{icdt}$ each time. In column (1) of Table 3.3 and Table 3.4 respectively, site visitors are the

reference category, in column (2) product viewers, in column (3) cart abandoners, and in column (4) previous buyers.

3.5.4.1 Click probability.

The segment dummies in column (1) of Table 3.3 show that keyword click probabilities are higher for product viewers (0.030, 95% CI [0.001, 0.058]) or previous buyers (0.053, 95% CI [0.021, 0.085]) than for site visitors but not for cart abandoners (0.031, 95% CI [-0.004, 0.064]). Column (2) shows that click probabilities are higher among previous buyers than product viewers (0.023, 95% CI [0.007, 0.040]). Column (3) reveals no significant differences between cart abandoners and product viewers (-0.001, 95% CI [-0.024, 0.023]) or cart abandoners and previous buyers (0.022, 95% CI [-0.004, 0.048]).

The coefficient estimates in columns (1)–(4) reveal significant position effects for all consumer segments (site visitors -0.343, 95% CI [-0.368, -0.318]; product viewers -0.291, 95% CI [-0.304, -0.278]; cart abandoners -0.293, 95% CI [-0.315, -0.271]; previous buyers -0.266, 95% CI [-0.284, -0.250]). Position has a negative influence on click probabilities, such that search ads in higher positions (i.e., lower value of the position variable) lead to a higher click probability than search ads in lower positions (i.e., higher values of the position variable). However, the coefficient decreases across columns from left to right, suggesting that the position effect weakens with progress in the buying process. The estimates for the interaction terms confirm this intuition statistically. In column (1), the position effect significantly diminishes from site visitors to product viewers (product viewers × position 0.052, 95% CI [0.027, 0.078]), cart abandoners (cart abandoners × position 0.050, 95% CI [0.019, 0.083]), and previous buyers (previous buyers × position 0.077, 95% CI [0.049, 0.105]). Compared to the position effect in the product viewer segment (column (2)), that for cart abandoners does not significantly differ (cart abandoners × position -0.002, 95% CI [-0.025, 0.021]), whereas the position effect for previous

buyers does (previous buyers × position 0.025, 95% CI [0.008, 0.042]). Compared with cart abandoners (column (3)), the ad's position has significantly less influence for previous buyers (previous buyers × position 0.026, 95% CI [0.001, 0.052]).

3.5.4.2 Conversion probability.

Independent of position, the specific consumer segment significantly contributes to conversion probabilities. Taking site visitors as a reference category (Table 3.4, column (1)), conversion probabilities increase with each further stage in the buying process (product viewers 0.695, 95% CI [0.470, 0.933]; cart abandoners 1.458, 95% CI [1.229, 1.705]; previous buyers 1.729, 95% CI [1.501, 1.970]). The differences between product viewers and cart abandoners on one side and product viewers and previous buyers on the other side are also significant in column (2) (cart abandoners 0.762, 95% CI [0.679, 0.843]; previous buyers 1.033, 95% CI [0.978, 1.090]). Moreover, previous buyers exhibit a higher conversion probability than cart abandoners in column (3) (previous buyers 0.272, 95% CI [0.192, 0.355]). Thus, conversion probabilities are higher in later stages.

The position variable coefficients in columns (1)–(4) reveal a positive position effect for site visitors (0.061, 95% CI [-0.158, 0.276]), cart abandoners (0.060, 95% CI [-0.017, 0.135]), and previous buyers (0.042, 95% CI [-0.012, 0.096]) but a negative effect for product viewers (-0.023, 95% CI [-0.077, 0.031]). However, none of these position effects is significant. The interaction effects instead reveal significant results; column (2) displays a positive significant interaction effect for previous buyers (previous buyers × position 0.064, 95% CI [0.006, 0.122]) and a marginal significant interaction effect for cart abandoners (cart abandoners × position 0.082, 95% CI [-0.001, 0.164]), such that the negative position effect for product viewers is attenuated and even becomes positive for previous buyers and cart abandoners.

Table 3.3. Model results, observational study: Estimates for click probability by stage in the buying process

	Consumer segment											
	(1) Site visitors			(2) Product viewers			(3) Cart abandoners			(4) Previous buyers		
	Coef.	(*SE*)	95% CI	Coef.	(*SE*)	95% CI	Coef.	(*SE*)	95% CI	Coef.	(*SE*)	95% CI
Constant	-2.875	(0.058)	[-2.990, -2.763]	-2.845	(0.057)	[-2.957, -2.753]	-2.846	(0.058)	[-2.960, -2.733]	-2.822	(0.057)	[-2.933, -2.713]
Consumer segments												
Site visitors				-0.030	(0.014)	[-0.058, -0.001]	-0.031	(0.017)	[-0.065, 0.003]	-0.053	(0.016)	[-0.084, -0.022]
Product viewers	0.030	(0.015)	[0.001, 0.058]				-0.001	(0.012)	[-0.024, 0.023]	-0.023	(0.008)	[-0.040, -0.007]
Cart abandoners	0.031	(0.018)	[-0.004, 0.064]	0.001	(0.012)	[-0.022, 0.025]				-0.022	(0.013)	[-0.048, 0.004]
Previous buyers	0.053	(0.016)	[0.021, 0.085]	0.023	(0.009)	[0.007, 0.040]	0.022	(0.013)	[-0.004, 0.048]			
Position	-0.343	(0.013)	[-0.368, -0.318]	-0.291	(0.007)	[-0.304, -0.278]	-0.293	(0.011)	[-0.315, -0.271]	-0.266	(0.009)	[-0.284, -0.250]
Interaction effects												
Site visitors × Position				-0.052	(0.013)	[-0.078, -0.026]	-0.050	(0.016)	[-0.082, -0.019]	-0.077	(0.014)	[-0.105, -0.048]
Procut viewers × Position	0.052	(0.013)	[0.027, 0.078]				0.002	(0.012)	[-0.021, 0.024]	-0.025	(0.009)	[-0.041, -0.008]
Cart abandoners × Position	0.050	(0.016)	[0.019, 0.083]	-0.002	(0.012)	[-0.025, 0.021]				-0.026	(0.013)	[-0.052, -0.001]
Previous buyers × Position	0.077	(0.015)	[0.049, 0.105]	0.025	(0.009)	[0.008, 0.042]	0.026	(0.013)	[0.001, 0.052]			
Quality score	0.034	(0.006)	[0.023, 0.044]	0.034	(0.006)	[0.022, 0.045]	0.034	(0.006)	[0.023, 0.045]	0.034	(0.006)	[0.023, 0.045]
Competition	0.168	(0.033)	[0.102, 0.233]	0.168	(0.034)	[0.101, 0.234]	0.168	(0.034)	[0.101, 0.235]	0.168	(0.033)	[0.104, 0.233]
Brand	0.039	(0.027)	[-0.013, 0.091]	0.039	(0.027)	[-0.015, 0.092]	0.039	(0.028)	[-0.015, 0.094]	0.038	(0.028)	[-0.015, 0.092]
Category	0.133	(0.031)	[0.072, 0.194]	0.133	(0.030)	[0.074, 0.192]	0.133	(0.030)	[0.073, 0.191]	0.133	(0.031)	[0.073, 0.194]
Tablet	0.030	(0.011)	[0.008, 0.052]	0.030	(0.011)	[0.009, 0.051]	0.030	(0.011)	[0.009, 0.051]	0.030	(0.011)	[0.008, 0.051]
Mobile	-0.179	(0.010)	[-0.197, -0.160]	-0.179	(0.009)	[-0.198, -0.161]	-0.179	(0.010)	[-0.197, -0.160]	-0.179	(0.010)	[-0.197, -0.160]
Week fixed effects	Yes			Yes			Yes			Yes		

Note. CI = Confidence interval.

Table 3.4. Model results, observational study: estimates for conversion probability by stage in the buying process

	Consumer segment								
	(1) Site visitors			(2) Product viewers			(3) Cart abandoners			(4) Previous buyers		
	Coef.	(*SE*)	95% CI	Coef.	(*SE*)	95% CI	Coef.	(*SE*)	95% CI	Coef.	*(SE)*	95% CI
Constant	-3.416	(0.156)	[-3.735, -3.110]	-2.721	(0.104)	[-2.921, -2.520]	-1.955	(0.109)	[-2.166, -1.742]	-1.687	(0.104)	[-1.891, -1.484]
Consumer segments												
Site visitors				-0.698	(0.117)	[-0.932, -0.474]	-1.461	(0.122)	[-1.705, -1.226]	-1.731	(0.121)	[-1.973, -1.500]
Product viewers	0.695	(0.119)	[0.470, 0.933]				-0.762	(0.041)	[-0.843, -0.680]	-1.034	(0.028)	[-1.089, -0.977]
Cart abandoners	1.458	(0.122)	[1.229, 1.705]	0.762	(0.042)	[0.679, 0.843]				-0.272	(0.043)	[-0.356, -0.189]
Previous buyers	1.729	(0.120)	[1.501, 1.970]	1.033	(0.029)	[0.978, 1.089]	0.272	(0.042)	[0.192, 0.355]			
Position	0.061	(0.111)	[-0.158, 0.276]	-0.023	(0.028)	[-0.077, 0.031]	0.060	(0.039)	[-0.017, 0.135]	0.042	(0.027)	[-0.012, 0.096]
Interaction effects												
Site visitors × Position				0.087	(0.113)	[-0.137, 0.308]	0.006	(0.118)	[-0.227, 0.231]	0.023	(0.113)	[-0.199, 0.240]
Procut viewers × Position	-0.085	(0.113)	[-0.305, 0.136]				-0.082	(0.041)	[-0.163, 0.000]	-0.064	(0.030)	[-0.123, -0.005]
Cart abandoners × Position	-0.002	(0.116)	[-0.228, 0.226]	0.082	(0.042)	[-0.001, 0.164]				0.017	(0.043)	[-0.066, 0.100]
Previous buyers × Position	-0.020	(0.113)	[-0.237, 0.202]	0.064	(0.030)	[0.006, 0.122]	-0.018	(0.041)	[-0.100, 0.062]			
Quality score	0.029	(0.010)	[0.008, 0.049]	0.029	(0.010)	[0.009, 0.049]	0.029	(0.010)	[0.008, 0.049]	0.029	(0.010)	[0.009, 0.049]
Brand	-0.034	(0.036)	[-0.105, 0.037]	-0.033	(0.036)	[-0.104, 0.035]	-0.034	(0.036)	[-0.103, 0.036]	-0.033	(0.036)	[-0.102, 0.037]
Category	--0.085	(0.040)	[-0.163, -0.007]	-0.085	(0.040)	[-0.163, -0.006]	-0.085	(0.040)	[-0.163, -0.006]	-0.086	(0.040)	[-0.164, -0.007]
Tablet	-0.569	(0.046)	[-0.659, -0.479]	-0.568	(0.046)	[-0.659, -0.477]	-0.569	(0.045)	[-0.660, -0.481]	-0.569	(0.046)	[-0.660, -0.479]
Mobile	-1.131	(0.047)	[-1.225, -1.038]	-1.131	(0.048)	[-1.223, -1.038]	-1.130	(0.049)	[-1.225, -1.036]	-1.131	(0.048)	[-1.227, -1.037]
Week fixed effects	Yes			Yes			Yes			Yes		

Note. CI = Confidence interval.

3.6 General Discussion

Google's introduction of RLSA opened new possibilities for firms to improve their SEA strategies and has proven highly popular already. Yet, there is no evidence of the impact of consumers' online shopping behavior on the effectiveness of SEA. With the current study, we seek to offer initial evidence in this new domain we label "SEA retargeting." We investigate how a consumer's stage in the buying process influences the effectiveness of different ad positions—the main lever of search ad effectiveness (Narayanan & Kalyanam, 2015). In line with theory on consumer preferences that asserts consumers with ill-defined preferences (i.e., in early stages of their buying process) to construe preferences on the spot and therefore to respond more strongly on cues such as rank-ordered formats (Simonson, 2005), our results show that higher ad positions have the strongest influence on click probabilities for consumers at the beginning of their buying process. This influence decreases gradually with each stage, except for cart abandoners. In the same way, consumers in early stages convert more in response to higher rather than lower ad positions, whereas consumers in later stages even exhibit a higher conversion probability after clicking on ads in lower than higher positions. Research on post-decision dissonance provides a potential explanation for this tendency: Uncertainty about a previous decision can create dissonance which consumers aim to resolve by seeking information in favor of that decision (Festinger, 1962). Thus, for example, previous buyers, who eventually bought from the firm, visit the search engine to reassure themselves that they made the right decision. For this, they use ads in higher positions as confirmatory evidence, click on them, but have no intentions to actually buy.

Our findings extend previous SEA research in two important ways. First, we offer a more fine-grained view on the influence of ad positions on consumers' click behavior. We show that the identified general negative position effect on click probabilities (Agarwal et al., 2011; Ghose & Yang, 2009) differs in strength between

different stages of the buying process. Second, our results help clarify ambiguous results about the influence of ad positions on consumers' conversion decision. Whereas Ghose and Yang (2009) identified a negative position effect, Agarwal et al. (2011) revealed a positive position effect, suggesting that consumers are more likely to purchase from lower rather than higher positioned ads. Based on our findings, we argue that the opposed position effects stem from different ratios of consumers in early stages with ill-defined preferences and a higher conversion probability from higher ad positions and consumers in later stages with more stable preferences and a higher conversion probability from lower ad positions.

Turning to the implications for firms, one needs to differentiate whether firms seek to maximize clicks or conversions. If firms are interested in generating more clicks, our implications are straightforward: firms should display their search ads in higher positions for consumers in early stages, because those consumer are more susceptible to ads in higher positions. If firms seek to increase the number of conversions bidding higher on keywords from consumers in early stages is also more effective due to the revealed position effects. In addition, this would be more efficient for increasing conversions compared to alternative positioning strategies, such as the one used by conventional business practice. Assuming that costs per click remain constant due to Google's second-price auction format, positioning ads higher for consumers in early stages would lead to more conversions with the same amount of budget invested. However, firms should not neglect the finding that conditional on click, consumers that are in later stages of the buying process have per se higher conversion probabilities. Accordingly, clicks from consumers in later stages are more valuable than those from consumers in early stages. Thus, firms must balance both the position effect and the effect of a consumer's stage when designing their bidding strategies. Balancing these two effects is also important for search engines. Search engines primarily generate revenues through consumers' clicks. Thus, at first sight, they should recommend a positioning strategy that

maximizes the overall number of clicks (i.e, ads in higher positions for consumers in early stages). However, they also need to acknowledge the effects of such a positioning strategy on the overall number of conversions to act in the interest of their firms and to guarantee the long-term success of their platforms.

Our research suggests promising directions for future research. Building on our findings, future research should for example investigate how firms should exactly balance the effects of ad positions and a consumer's stage in the buying process to maximize overall clicks and conversions with a given budget, thereby also accounting for firm-specific parameters. Researchers should also investigate how consumers' prior online shopping behavior influences their keyword use in search queries or their response to ad content, both of which have been demonstrated to be important levers of search ad effectiveness besides ad positions (Agarwal et al., 2011; Rutz & Trusov, 2011). Additionally, RLSA allows to extend previous knowledge on interdependencies between paid and organic search results, a heavily-debated topic in extant SEA research (Blake, Nosko, & Tadelis, 2015; Yang & Ghose, 2010). Finally, the RLSA technology offers more fine-grained segmentation criteria than the buying process stage. Thus, researchers could collect rich data on consumers' prior online shopping behavior and subsequent search queries to investigate their interplay and identify potential cross- and up-selling opportunities in SEA.

3.7 References

Agarwal, A., Hosanagar, K., & Smith, M. D. (2011). Location, location, location: An analysis of profitability of position in online advertising markets. *Journal of Marketing Research*, *48*, 1057–1073. https://doi.org/10.1509/jmr.08.0468

Animesh, A., Viswanathan, S., & Agarwal, R. (2011). Competing “creatively” in sponsored search markets: The effect of rank, differentiation strategy, and competition on performance. *Information Systems Research*, *22*, 153–169. https://doi.org/10.1287/isre.1090.0254

Blake, T., Nosko, C., & Tadelis, S. (2015). Consumer heterogeneity and paid search effectiveness: A large-scale sield experiment. *Econometrica*, *83*, 155–174. https://doi.org/10.3982/ECTA12423

Bleier, A., & Eisenbeiss, M. (2015). Personalized online advertising effectiveness: The interplay of what, when, and where. *Marketing Science*, *34*, 669–688. https://doi.org/10.1287/mksc.2015.0930

Brooks, S. P., & Gelman, A. (1998). General methods for monitoring convergence of iterative simulations. *Journal of Computational and Graphical Statistics*, *7*, 434–455. https://doi.org/10.2307/1390675

Bucklin, R. E., & Sismeiro, C. (2003). A model of web site browsing behavior estimated on clickstream data. *Journal of Marketing Research*, *40*, 249–267. https://doi.org/10.1509/jmkr.40.3.249.19241

Festinger, L. (1962). *A theory of cognitive dissonance* (Vol. 2): Stanford university press.

Gelman, A., Jakulin, A., Pittau, M. G., & Su, Y.-S. (2008). A weakly informative default prior distribution for logistic and other regression models. *The Annals of Applied Statistics*, *2*, 1360–1383. https://doi.org/10.1214/08-AOAS191

Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science*, *7*, 457–472. https://doi.org/10.1214/ss/1177011136

Ghose, A., Goldfarb, A., & Han, S. P. (2013). How is the mobile internet different? Search costs and local activities. *Information Systems Research*, *24*, 613–631. https://doi.org/10.1287/isre.1120.0453

Ghose, A., & Yang, S. (2009). An empirical analysis of search engine advertising: Sponsored search in electronic markets. *Management Science*, *55*, 1605–1622. https://doi.org/10.1287/mnsc.1090.1054

Google. (2016). Reach the right audiences with RLSA: Google best practices. Retrieved from https://support.google.com/adwords/answer/6167113

Google. (2018a). About remarketing lists for search ads. Retrieved from https://support.google.com/google-ads/answer/2701222?hl=en

Google. (2018b). Keyword-Planer. Retrieved from https://ads.google.com/intl/de_de/home/tools/keyword-planner/

Jeziorski, P., & Moorthy, S. (2018). Advertiser prominence effects in search advertising. *Management Science*, *64*, 1365–1383. https://doi.org/10.1287/mnsc.2016.2677

Johnson, G. A., Lewis, R. A., & Nubbemeyer, E. I. (2017). Ghost ads: Improving the economics of measuring online ad effectiveness. *Journal of Marketing Research*, *54*, 867–884. https://doi.org/10.1509/jmr.15.0297

KPMG. (2017). The truth about online consumers: 2017 global online consumer report. Retrieved from https://assets.kpmg.com/content/dam/kpmg/xx/pdf/2017/01/the-truth-about-online-consumers.pdf

Lambrecht, A., & Tucker, C. (2013). When does retargeting work? Information specificity in online advertising. *Journal of Marketing Research*, *50*, 561–576. https://doi.org/10.1509/jmr.11.0503

Merkle. (2018). *Digital marketing report: Deep market insights to drive smarter media investments.*

Moriguchi, T., Xiong, G., & Luo, X. (2016). Retargeting ads for shopping cart recovery: Evidence from online field experiments. Retrieved from https://ssrn.com/abstract=2847631

Narayanan, S., & Kalyanam, K. (2015). Position effects in search advertising and their moderators: A regression discontinuity approach. *Marketing Science*, *34*, 388–407. https://doi.org/10.1287/mksc.2014.0893

Rutz, O. J., & Bucklin, R. E. (2011). From generic to branded: A model of spillover in paid search advertising. *Journal of Marketing Research*, *48*, 87–102. https://doi.org/10.1509/jmkr.48.1.87

Rutz, O. J., & Trusov, M. (2011). Zooming in on paid search ads—A consumer-level model calibrated on aggregated data. *Marketing Science*, *30*, 789–800. https://doi.org/10.1287/mksc.1110.0647

Sahni, N. S., Narayanan, S., & Kalyanam, K. (2018). *An experimental investigation of the effects of retargeted advertising - The role of frequency and timing*. *Journal of Marketing Research*.

Shankar, V., & Malthouse, E. C. (2007). The growth of interactions and dialogs in interactive marketing. *Journal of Interactive Marketing*, *21*, 2–4. https://doi.org/10.1002/dir.20080

Simonson, I. (2005). Determinants of customers' responses to customized offers: Conceptual framework and research propositions. *Journal of Marketing*, *69*, 32–45. https://doi.org/10.1509/jmkg.69.1.32.55512

Yang, S., & Ghose, A. (2010). Analyzing the relationship between organic and sponsored search advertising: Positive, negative, or zero interdependence? *Marketing Science*, *29*, 602–623. https://doi.org/10.1287/mksc.1090.0552

4. Study 3: "Why Would I Read a Mobile Review?" Device Compatibility Perceptions and Effects on Perceived Helpfulness

Armin März, Sebastian Schubach, Jan H. Schumann

Published in *Psychology & Marketing* (VHB-Ranking: B)

The proliferation of mobile devices means that mobile-generated customer reviews are on the rise, though research into their peculiarities and appraisals is rare. With field data and a scenario experiment, the current research demonstrates how recipients perceive mobile-generated customer reviews fundamentally differently from nonmobile-generated reviews. First, behavioral field data provide evidence that consumers discount the helpfulness of mobile reviews due to their text-specific content and style particularities. Second, the scenario experiment shows that identifying a review as written on a mobile device lowers recipients' perceptions of its value, but only if they use a nonmobile device to read the review. Recipients rely on device information as a source cue to assess compatibility. If they perceive themselves as compatible with the device, recipients perceive the review as more helpful because they attribute the review's content to the quality of the reviewed object; if they regard it as incompatible, recipients assume the review reflects the personal dispositions of the reviewer and discount its helpfulness. Managers of online opinion platforms thus must acknowledge the peculiarities of mobile-generated reviews and the impact of tagging content as mobile or not.

4.1 Introduction

On pace with the widespread adoption of mobile devices (Nielsen, 2013), mobile customer reviews—defined as peer-generated evaluations of a product or company (Mudambi & Schuff, 2010) created with a mobile device (Palka, Pousttchi, & Wiedemann, 2009)—are on the rise. Customers employing their mobile devices anytime and anywhere (Balasubramanian, Peterson, & Jarvenpaa, 2002) share their experiences with other potential customers in real time (Hennig-Thurau et al., 2010). Firms encourage such practices, asking customers to rate and review their experiences while on the go. Yet despite this span and potential influence, little evidence specifies the precise effects of mobile customer reviews on other consumers. Do recipients perceive mobile reviews as more authentic or helpful because they reflect an immediate consumption experience? Or do they dismiss them because mobile reviews tend to be shorter and laden with affect?

Prior research on customer reviews in general does not answer these questions. Studies mainly address how aggregate characteristics of reviews on a review platform, such as average ratings or total number of reviews, influence sales (Zhu & Zhang, 2010), or else how individual review characteristics such as valence (Sen & Lerman, 2007; Wu, 2013), textual characteristics (Ludwig et al., 2013; Scholz & Dorner, 2013), or cues (Chen & Lurie, 2013; Forman, Ghose, & Wiesenfeld, 2008; Naylor, Lamberton, & Norton, 2011) influence the helpfulness and conversion rates associated with reviews. Such investigations do not address potential differences across communication channels though (Berger, 2014). When studies consider the uses of mobile devices, they primarily investigate the motives that drive senders to undertake word-of-mouth (WOM) behavior, without any specific focus on mobile reviews or their perception (Okazaki, 2008; Palka et al., 2009). Lurie, Ransbotham, and Liu (2014) offer some notable insights though; for example, they show that mobile reviews differ from nonmobile reviews in their content-specific characteristics, such that some of them increase perceived helpfulness, while others

decrease it. These authors also show that mobile reviews exert negative effects on recipients' value perceptions, simply because they are mobile. However, Lurie et al. (2014) do not include style-specific elements that appear in recent research into online customer reviews (Ludwig et al., 2013; Schindler & Bickart, 2012). Nor do they elaborate on how and why mobile reviews might affect recipients' appraisals.

The current study extends research on customer helpfulness perceptions of mobile reviews by using both a field study (Study 1) and a scenario-based experiment (Study 2). Studying helpfulness perceptions as outcome variable is common in research on online customer reviews (Forman et al., 2008; Mudambi & Schuff, 2010) and in line with the increased concerns of online customer review platforms in providing helpful reviews. Platforms such as Amazon proactively ask users to rate the helpfulness of single reviews and even change their sorting mechanisms in order to display helpful reviews in higher positions (Mudambi & Schuff, 2010). The helpfulness of a review is supposed to reflect its informational value (Chen & Lurie, 2013) which in turn can influence customers' purchase intentions for the reviewed product (S. Moore, 2015) or actual purchase behavior (Yao, Yuan, Qian, & Xu, 2016).

Study 1 leverages findings that show that style-specific aspects of review texts are an important predictor of the perceived helpfulness of customer reviews. The findings confirm that including style criteria in analyses of online reviews yields a better understanding of the perceived helpfulness of mobile reviews because style-specific characteristics differ significantly across review channels and influence the perceived helpfulness of a review. However, and in line with the results of Lurie et al. (2014), a negative effect of mobile reviews persists beyond the contribution of these style-specific characteristics. Therefore, Study 2 adopts a scenario-based, online approach, holding the content and style of one review constant over various experimental conditions that manipulate only the information about the device used to write the review. If the device used to create the review is congruent with the

device used to read it, recipients sense compatibility and perceive the review as more helpful because they attribute the motivation for the review to the reviewed product or service. However, perceptions of incompatibility lead recipients to assume the review reflects the personal dispositions of the reviewer to a greater extent, such that it appears less helpful. Therefore, empirical evidence affirms that the device used to create a review has an indirect effect on helpfulness perceptions, through compatibility considerations and attributions by the recipient, which goes beyond the influence of content- and style-specific characteristics of an online customer review.

These findings contribute to theory in multiple, relevant ways. First, this study contributes to research on how technology shapes the creation and reception of WOM (Berger, 2014). Second, this study extends research on source cues and the way they work in the context of customer reviews (Forman et al., 2008; Naylor et al., 2011). Third, the present study contributes to research on compatibility perceptions in the context of technology usage (Kleijnen, de Ruyter, & Wetzels, 2007; G. Moore & Benbasat, 1991). Fourth, this study introduces style characteristics in research on review helpfulness (Lurie et al., 2014; Scholz & Dorner, 2013). The findings also may prove valuable for managers of online opinion platforms, who should recognize that mobile reviews appear less helpful, due to their style and content peculiarities. Using a device tag to promote a mobile application or disclose the context of the review creation (Seave, 2013) even can induce a “boomerang effect” if recipients sense incompatibility.

After a brief overview of prior research on mobile reviews, this article continues with a field study (Study 1) and its results. The findings of Study 1 provide a foundation for the conceptual framework for Study 2, tested in a scenario-based experiment. Finally, the authors discuss the results and their implications for research and practice.

4.2 Study 1: Different Style and Content of Mobile Versus Nonmobile Reviews

4.2.1 Theoretical background.

Channel characteristics shape what people discuss and how they talk about it in their WOM (Berger & Iyengar, 2013), though mobile-specific characteristics remain relatively unknown. To investigate whether mobile versus nonmobile customer reviews differ in their creation or perceptions, Lurie et al. (2014) argue that the particularities of the creation process for mobile reviews—namely, the possibility of real-time engagement, the high physical and cognitive costs of creation due to the small screen and keyboard sizes, and the strong personal ties to the mobile device—influence the way mobile reviewers write about and rate a particular review topic. Their evidence that mobile and nonmobile reviews differ, according to field data from a restaurant review platform, specifies that mobile reviews are shorter, are less extreme but negative in their ratings, contain more affective and less cognitive cues, and use one-sided negative or positive language. They also report more current concerns (e.g., work, money) and fewer social aspects (e.g., references to other people). Many of those content-specific characteristics influence how recipients perceive reviews. For example, recipients perceive reviews with fewer words, less extreme ratings, and fewer social aspects as less helpful; other content-specific aspects do not exhibit significant effects though. In another intriguing finding, Lurie et al. (2014) note that mobile reviews—identified by a symbol—earn less helpful ratings, even after controlling for content-specific characteristics and rating- or reviewer-specific aspects. In this work, Lurie et al. (2014) focus on content words, which are valuable for assessing the basic information contained in a textual element. However, they do not determine the style of a text-based communication, that is, how senders convey information to recipients (Ireland & Pennebaker, 2010). Yet Ludwig et al. (2013) note that writing style is crucial in determining the appraisal of customer reviews.

Study 1 therefore extends the research framework proposed by Lurie et al. (2014) by introducing function words and verbal immediacy as two central style elements of customer reviews. The goal is to determine if including style-specific review text characteristics helps explain the negative mobile effect identified by Lurie et al. (2014).

4.2.2 Hypotheses development.

4.2.2.1 Style characteristics: Mobile versus nonmobile reviews.

Linguistic style is specific to the context (Niederhoffer & Pennebaker, 2002), so style elements should vary significantly across mobile and nonmobile customer reviews because mobile and nonmobile devices differ in their form and tend to be used in different situations (Lurie et al., 2014). For example, function words help readers evaluate customer reviews (Ludwig et al., 2013). These pronouns, prepositions, articles, conjunctions, or auxiliary verbs reveal the relationships of the sender to the topic of communication or among content constituents (Tausczik & Pennebaker, 2010). For example, senders use pronouns (e.g., “I,” “it,” “here”) to refer to other persons, objects, places, or time. Prepositions often provide more concrete information about a topic (Chung & Pennebaker, 2007; Tausczik & Pennebaker, 2010). The physical and cognitive costs of writing on mobile devices likely leads to the use of varying numbers of function words in mobile versus nonmobile reviews. Consumers have learned to write short messages on mobile phones and rely on character restrictions, such as abbreviations and acronyms (Grinter & Eldridge, 2003; Ling & Baron, 2007), so their word usage is limited and closely considered (Lurie et al., 2014). Furthermore, mobile devices are more convenient for quick, immediate responses than for elaborated responses. Therefore, mobile reviews likely are characterized by fewer function words, which are unnecessary, relative to the key content.

H_1: Mobile customer reviews include fewer function words than nonmobile customer reviews.

Verbal immediacy is another stylistic factor that likely differs between mobile and nonmobile reviews due to the real-time nature of mobile communication. Verbal immediacy is characterized by the use of "concrete, personal, involved, experiential language with a focus on the here and now" (Borelli, Sbarra, Mehl, & David, 2011, p. 342). Verbal immediate language uses first-person singular, present tense, and discrepancies but fewer articles and long words (Pennebaker & King, 1999). Such language is especially common in high attachment and high-involvement situations (Borelli et al., 2011; Mehrabian, 1967). Mobile devices enable continuous, immediate communication that overcomes spatial and temporal constraints and helps address contextual search tasks, so mobile reviewers tend to be very involved in the situation (Okazaki & Mendez, 2013). The ubiquity of mobile devices also allows users to communicate in motion, anywhere, anytime, leading to highly personal relationships between users and their devices (Shankar, Venkatesh, Hofacker, & Naik, 2010). Thus, verbal immediacy should be higher for mobile than for nonmobile reviews.

H_2: Mobile customer reviews feature greater verbal immediacy than nonmobile customer reviews.

4.2.2.2 Perceived helpfulness of style-specific characteristics.

Prior research on online consumers indicates that they value relevant information in reviews that enables them to evaluate a product, its quality, and its performance (Jiang & Benbasat, 2004). Media richness theory (Daft & Lengel, 1986) suggests that relevance is a function of the amount and richness of the information: The amount guarantees the completeness of the information provided, and its richness reduces ambiguity in the information, such as the possibility of multiple

interpretations (Daft & Macintosh, 1981). In customer review contexts, content elements (e.g., number of words) reflect the completeness of the information, which should have positive effects on review helpfulness (Mudambi & Schuff, 2010). Style elements contribute directly to information richness by providing ways to interpret the review without altering the informational content (Ludwig et al., 2013). Thus, information richness, and accordingly, reviews' perceived helpfulness, should vary with function words and verbal immediacy as linguistic style elements.

First, function words clarify the relationship between content elements. The use of prepositions and conjunctions helps communicators elaborate on complex facts and combine multiple thoughts, thereby increasing the coherence of their narrative (Graesser, McNamara, Louwerse, & Cai, 2004). Using the example of academic manuscripts, Hartley, Pennebaker, and Fox (2003) show that the amount of function words is highest in the discussion section, which abstracts the results and integrates them with existing evidence. When narrative coherence is greater, it becomes easier for less-knowledgeable recipients to acquire understanding about the communication content (McNamara, Kintsch, Songer, & Kintsch, 1996). Therefore, the use of function words should give readers a more fine-grained and unambiguous picture of the object and situation being reviewed, even though full understanding of function words might demand shared social and context knowledge between communication partners (Chung & Pennebaker, 2007). Thus, customer reviews with more function words should be more helpful to recipients than customer reviews with fewer function words.

H_3: The number of function words has a positive effect on consumers' perceptions of the helpfulness of customer reviews.

Second, as Bradac, Bowers, and Courtright (1979) claim, communication content high in verbal immediacy positively influences receivers' judgments of a source's competence, by serving as a proxy for the communicator's positive attitude

toward the communication object. However, recipients need to be physically present or have knowledge of the communication situation to be able to infer a communicator's attitude toward the content by gauging the use of language high in verbal immediacy (Mehrabian, 1968). In a review situation, recipients usually lack this specific knowledge about the situation described, and they rarely share realities with the reviewer, especially in the anonymous context of review platforms. Thus, verbal immediate language cannot help recipients assess reviewers' attitudes toward the reviewed subject. According to Pennebaker, Mehl, and Niederhoffer (2003) and Wiener and Mehrabian (1968), language high in verbal immediacy rather makes it difficult for recipients to get a clear and unambiguous picture of the specific review situation. Communicators high in verbal immediacy draw more on the shared realities of the communication partners than do communicators low in verbal immediacy. The egocentric perspective of verbal immediate language, due to the use of first-person singular, also makes it difficult for receivers to draw accurate inferences about the communicated content. Therefore, information provided through reviews with higher verbal immediacy should be more ambiguous than information provided in reviews with lower verbal immediacy. Following media richness theory, reviews displaying higher verbal immediacy in turn should be less helpful to the readers, compared with reviews with lower verbal immediacy.

H_4: Recipients perceive customer reviews as less helpful when their verbal immediacy is greater.

4.2.3 Empirical context.

The tests of the proposed hypotheses rely on data from the former German opinion and recommendation platform Qype, which was acquired by Yelp in October 2012. Registered users could write reviews about local businesses and institutions in various categories, anonymously with a pseudonym. The platform used a five-star rating scale and allowed reviewers to write reviews of any length, on the web site or,

since April 2009, through a mobile application. It tagged mobile reviews with a symbol to promote its mobile application. Registered users could compliment other users' reviews but only through the web site, not when using the mobile application. Thus, compliments can be assigned unambiguously to recipients using a nonmobile channel, which provides a means to exclude the potential confounding effects caused by the device used to read the review, a factor that otherwise would have been unobservable.

4.2.4 Data collection.

The real reviews, collected from a public web site, were analyzed on an individual basis. The platform maintained an application programing interface that enabled the collection of review texts, ratings, check-ins, timestamps, and information about reviewers and reviewed locations. A self-developed script also crawled the web site content to gather mobile tags, that is, information about whether a review had been written with the mobile app. In total 315,648 customer reviews were collected. Applying a criterion that requires users to have generated reviews after the introduction of the mobile application in April 2009 and since then using mobile and nonmobile devices (i.e., switched devices at least once) produced a subsample of 55,112 reviews by 5,191 users. This criterion reduced reviewer-specific effects, which might reflect different usage behaviors by people who only use one device (Lurie et al., 2014) or who changed their overall review behavior with the introduction of the mobile application. The final sample features 44.05% mobile and 55.95% nonmobile reviews. The reviews referred to 54,883 unique locations in 12 categories, and the restaurant category yielded more than one-third of the total number of reviews.

4.2.5 Real-time assumption.

To confirm that users create reviews on their mobile devices in real time, the present study gathered check-in time data, as a proxy for the moment of the service experience. Similar to other social media applications (e.g., Foursquare, Facebook Places), check-ins allowed users to indicate on their mobile devices (but not nonmobile devices) that they had entered a specific location. Users also could check in independently of a review, such that they visited, checked in, left and wrote a review afterward (using a mobile or nonmobile device). To determine how often users did so, the 13,333 collected check-ins were merged with the subsample of collected consumer reviews to define the temporal distance between the check-in time and the time of review creation, according to their respective timestamps. If multiple check-ins appeared, this study used the closest temporal distance between timestamps. The results of this merger showed that 26.3% of the matched reviews were written before a check-in and 73.3% after a user checked in to a place. Among the latter, 55.0% were created on mobile devices and 45.0% on nonmobile devices. Of all mobile reviews, consumers wrote 54.2% within an hour of their check-in and 81.9% within 24 hours. In contrast, consumers generated less than one-third (30.1%) of the nonmobile reviews within 24 hours of their check-in and only 2.0% within the first hour. Considering just the first week after a check-in, to reduce bias due to outliers, the mean temporal distance between check-in and mobile review creation was 9.03 hours (SD = 25.05), whereas that for nonmobile reviews was 44.91 hours (SD = 45.75), yielding a significant difference ($t(3{,}759) = 38.36$, $p < 0.001$). This initial empirical evidence suggests that users write mobile reviews sooner after a service experience than nonmobile reviews, thus confirming the real-time assumption proposed but not empirically tested by Hennig-Thurau et al. (2010) and Lurie et al. (2014).

4.2.6 Measures.

4.2.6.1 Style characteristics.

The analyses of the style characteristics relied on the German dictionary in the Linguistic Inquiry and Word Count (LIWC) text analysis program (Pennebaker, Booth, & Francis, 2007; Wolf et al., 2008).[1] This program quantifies the proportion of words in a text that belong to predefined linguistic or psychometric categories and informs assessments of writing styles in many prior marketing research studies (Barasch & Berger, 2014; Ludwig et al., 2013). Tang and Guo (2015) affirm the validity and utility of LIWC for studying WOM communication, too. The German dictionary comprises approximately 7,600 words and word stems, each assigned to one or more of 68 categories. With *function words* and *verbal immediacy*, the current study considers two of these categories. *Function words* reflect the total share of all pronouns, articles, prepositions, numbers, and expressions of negation or assent in the review text (M = 23.37, SD = 8.96). *Verbal immediacy* is the arithmetic mean of the proportion of first-person singular pronouns, present tense verbs, and discrepancies (e.g., “should,” “could,” “but”), as well as of the inverse counts of both words with more than six letters and articles (Pennebaker & King, 1999) in the review text. A higher verbal immediacy score implies a more personal, immediate language style (Bazarova, Taft, Choi, & Cosley, 2012).

4.2.6.2 Mobile.

The present study also seeks to determine if the “mobile effect” originally revealed by Lurie et al. (2014) still holds, even after introducing style criteria. Therefore, the analysis includes a binary variable (1 = mobile, 0 = nonmobile).

[1] Differences between the current study and Lurie et al. (2014) mainly reflect different word classifications between the German dictionary, based on the 2001 English LIWC, and the 2007 English LIWC. Pennebaker and King (1999) offer empirical evidence of the high correlation between these two versions though, and Wolf et al. (2008) verify strong equivalence between the German and English LIWC 2001 in most linguistic categories. Still, they leave open the question of whether the categories in the German version validly reflect the original psychological constructs.

Mobile means the review was written in the mobile application; nonmobile indicates it was written with the browser version of the platform.

4.2.6.3 Perceived helpfulness.

Qype users could value a review because it is “useful,” “funny,” or “well written”; confirms their existing ideas; or makes them seek “more like this.” Readers saw the total number of compliments without further distinction. This study uses this total number as a proxy for perceived helpfulness.

4.2.7 Control variables.

To demonstrate the importance of style variables, beyond content criteria, this study also includes Lurie et al.‘s (2014) content measures in the models as covariates. Similar to the style criteria, measures were operationalized based on the LIWC. *Review length* is the number of words in each review. *Affective content* refers to the percentage of expressions of positive and negative emotions. *Cognitive mechanisms* comprise the proportion of words that reflect causation, insight, inhibition, discrepancy, tentativeness, or certainty. The measure of *current concerns* counts the share of words referring to jobs, achievement, leisure, home, or money. *Social processes* reflect the concerns of the reviewer about others, expressed by the share of words that refer to communication or others, such as friends or family, not to the self. *Valence* is the number of stars (1–5) assigned to a review. *Rating extremity* is operationalized as a binary variable, such that a very bad (1) or very good (5) rating earns a value of 1, and all other ratings take a value of 0.[2] Finally, the *one-sided sentiment* measure assigns reviews a value of 1 if they contain only positive or only negative emotion words and 0 if they contain no or both emotional sentiments.

[2] The five-star rating scale deviates from the 4-point scale in Lurie et al. (2014).

Other review-, reviewer-, and location-specific characteristics associated with the review might influence recipients' appraisals. Older reviews have had more time to attract compliments from other community members, so this analysis controls for *review age* (Chen & Lurie, 2013; Lurie et al., 2014), measured as the number of days between the actual date of the review's creation and the last day of the data collection. *Reviews per user* is operationalized as the total number of written reviews per user. The total number of reviews about each place is included as *reviews per location*. Including *category* fixed effects helps account for the different categories (12 unequivocal, 1 "other" category to refer to places that could be classified into different categories simultaneously) in the data set. Thus, 13 category dummies were created. To control for positive skew, the review age, review per user, and review per location variables were log transformed.

Multicollinearity should not be a threat in this study because (1) none of the variables correlated very highly (maximum = 0.61); (2) the average tolerance value was greater than 0.10 (M = 0.86; minimum = 0.77); and (3) the maximum variance inflation factor was well below the threshold of 10.0 (Hair, Black, Babin, & Anderson, 2014).

4.2.8 Specification.

The test for differences between mobile and nonmobile reviews relied on mean comparisons. The variances are unequal for the two groups, which calls for Satterthwaite corrected *t*-tests. The model of perceived helpfulness uses a zero-inflated negative binomial regression because the count of compliments in the data is skewed toward zero (73.5% of all observations received no compliments, and among observations with compliments 35.6% received one). In addition to these excessive zeros, the variance (40.19) of compliments clearly exceeds the mean (1.73), suggesting the need for a negative binomial regression (Greene, 2012). Zero-inflated negative binomial regression models can jointly estimate a logistic

regression with predictions of the probability for attracting zero compliments and a negative binomial regression that estimates the effects of the proposed content and style characteristics on perceived helpfulness. Because this study seeks to identify the effect of content and style characteristics on perceived helpfulness, this discussion focuses on the negative binomial regression results. The model is specified as:

$$perceived\ helpfulness_{ijkl} = \exp\big[\alpha_0 + \beta_1(function\ words_i) + \beta_2(verbal\ immediacy_i) + \beta_3(mobile_i) + \psi'_{ijk}X_{ijk} + \Omega'_{ijk}Y_{ijk} + \alpha_l + \varepsilon_{ijkl}\big],$$

where *i* refers to the review; *j* is the reviewer; *k* indicates the location; *l* is the category; X_{ijk} subsumes Lurie et al.'s (2014) content measures; Y_{ijk} is the vector of review-, reviewer-, and location-specific controls; α_l represents category dummies; and ε_{ijkl} is the error term.

4.2.9 Results.

4.2.9.1 Mean comparisons.

Table 4.1 contains the results for the mean comparisons of style criteria across mobile and nonmobile reviews. Mobile reviews use fewer function words (M_{mobile} = 21.89, $M_{nonmobile}$ = 24.53, $t(42{,}071) = -33.48$, $p < 0.001$) and are more personal and verbally immediate (M_{mobile} = −5.34, $M_{nonmobile}$ = −5.43, $t(45{,}492) = 3.95$, $p < 0.001$), in support of H_1 and H_2.

4.2.9.2 Perceived helpfulness.

Table 4.2 offers the results of the negative binomial regression models. The analysis follows a stepwise approach, starting in Model 1 with the proposed style variables in H_3 and H_4. Model 2 adds the mobile effect, and Model 3 includes Lurie et al.'s (2014) content controls. Model 4 further controls for review-, reviewer-, location-, and category effects.

In line with the proposed effects in H_3 and H_4, in Model 1, function words and verbal immediacy both significantly influence the perceived helpfulness of a review. Function words increase perceived helpfulness ($\beta_1 = 0.109$, $p < 0.001$), whereas higher verbal immediacy decreases helpfulness perceptions ($\beta_2 = -0.095$, $p < 0.001$). In Model 2, function words and verbal immediacy still exhibit significant positive ($\beta_1 = 0.092$, $p < 0.001$) and significant negative ($\beta_2 = -0.101$, $p < 0.001$) influences on perceived helpfulness, whereas the effect of mobile reviews on helpfulness perceptions is negative and significant ($\beta_3 = -1.084$, $p < 0.001$). The direction and significance of the proposed effects remains stable throughout Model 3 ($\beta_1 = 0.009$, $p < 0.001$; $\beta_2 = -0.073$, $p < 0.001$; $\beta_3 = -0.634$, $p < 0.001$) and Model 4 ($\beta_1 = 0.005$, $p = 0.001$; $\beta_2 = -0.024$, $p < 0.001$; $\beta_3 = -0.359$, $p < 0.001$), thus confirming H_3 and H_4 and suggesting that the mobile effect is prevalent even after controlling for style and content criteria. Including content criteria and review-, reviewer-, and location-specific controls increases McFadden's pseudo-R^2 value (Model 2 = 0.040; Model 3 = 0.089; Model 4 = 0.151) and decreases the Bayesian information criterion (Model 2 = 133,059; Model 3 = 126,454; Model 4 = 118,284), which confirms the importance of the suggested covariates. Looking specifically at the content variables provides evidence that review length, valence, and rating extremity increase perceived helpfulness. However, increases in affective content, cognitive mechanisms, and current concerns decrease perceived helpfulness. No significant results emerge for the relationship between one-sidedness or socially focused language with perceived helpfulness. In combination with the mean differences between mobile and nonmobile reviews (Table 4.1), the results show that mobile particularities decrease review helpfulness.

The tests of the models with z-standardized variables provide basically identical results. The estimates with a negative binomial regression provide results in the same direction, but the Vuong test of both distributions reveals $V = 21.056$ (Model 4, $p < 0.001$), such that the zero-inflated negative binomial regression fits

better than the negative binomial regression (Greene, 2012). The Lagrange multiplier score (Model 4, $\chi^2(1) = 14{,}460$, $p < 0.001$) for the zero-inflated model with the dispersion parameter fixed at zero confirms overdispersion and the decision to use a zero-inflated negative binomial model, not a zero-inflated Poisson model (Greene, 2012).

Table 4.1. Mean comparison of review characteristics between mobile and nonmobile reviews

	Total (*N* = 55,112)		Mobile reviews (*N* = 24,278)		Nonmobile reviews (*N* = 30,834)			
	Mean	*SD*	Mean	*SD*	Mean	*SD*	*t*-Value[a, b]	*r*
Perceived helpfulness	1.73	6.34	0.54	2.86	2.67	7.96	*t*(40,417) = -43.52***	0.21
Function words	23.37	8.96	21.89	10.44	24.53	7.40	*t*(42,071) = -33.43***	0.16
Verbal immediacy	-5.39	2.69	-5.34	3.02	-5.43	2.39	*t*(45,492) = 3.95***	0.02
Review length	71.87	90.25	43.90	54.83	93.88	105.32	*t*(48,427) = -71.87***	0.31
Affective content	6.77	6.42	7.94	7.75	5.85	4.94	*t*(39,143) = 36.56***	0.18
Cognitive mechanism	8.24	5.84	8.46	6.91	8.07	4.83	*t*(41,693) = 7.42***	0.04
Current concerns	6.29	6.29	6.67	7.31	5.99	5.34	*t*(42,943) = 12.21***	0.06
Social processes	4.28	4.08	4.01	4.59	4.49	3.61	*t*(45,198) = -13.44***	0.06
Valence	3.90	1.26	3.84	1.30	3.94	1.22	*t*(50,505) = -9.31***	0.04
Rating extremity[c]	0.51	0.50	0.52	0.50	0.51	0.50		
One-sided sentiment[c]	0.54	0.50	0.58	0.49	0.50	0.50		
Review age (in days)	340.00	285.57	301.80	238.50	370.10	314.50	*t*(55,034) = -29.01***	0.12
Reviews per user	58.20	109.77	36.52	67.23	75.27	131.60	*t*(47,967) = -44.80***	0.20
Reviews per location	4.45	9.66	4.35	9.41	4.53	9.85	*t*(53,120) = -2.16*	0.01

Note. [a]Variances are unequal for both groups, so the Satterthwaite corrected *t*-test was adapted. [b]No group comparisons were executed for binary variables. [c]Mean values reflect the proportions of reviews with extreme ratings and one-sided sentiments in the total sample.
* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 4.2. Zero-inflated negative binomial regression on perceived helpfulness

	Model 1		Model 2		Model 3		Model 4	
	Coeff. *z*-Value	*SE*	Coeff. *z*-Value	*SE*	Coeff. *z*-Value	*SE*	Coeff. *z*-Value	*SE*
Function words	0.109*** 55.676***	0.002	0.092*** 46.299***	0.002	0.009*** 3.971***	0.002	0.005** 2.541**	0.002
Verbal immediacy	-0.095*** -14.914***	0.006	-0.101*** -15.083***	0.007	-0.073*** -11.407***	0.006	-0.024*** -3.987***	0.006
Mobile			-1.084*** -32.626***	0.033	-0.634*** -20.832***	0.030	-0.359*** -12.902***	0.028
Controls								
Review length (words/100)					0.606*** 34.278***	0.018	0.459*** 33.746***	0.014
Affective content					-0.056*** -15.612***	0.004	-0.021*** -5.895***	0.004
Cognitive mechanism					-0.030*** -8.447***	0.004	-0.016*** -4.850***	0.003
Current concerns					-0.031*** -9.978***	0.003	-0.020*** -6.950***	0.003
Social processes					-0.010* -2.227*	0.004	0.002 0.474	0.004
Valence					0.165*** 14.524***	0.011	0.010*** 9.671***	0.010
Rating extremity					-0.017 -0.615	0.027	0.087*** 3.482***	0.025
One-sided sentiment					0.020 0.733	0.027	-0.041 -1.635	0.025
Review age (log)							0.162*** 17.317***	0.009
Reviews per user (log)							0.720*** 63.078***	0.011
Reviews per location (log)							0.080*** 6.113***	0.013
Category fixed effects							included	
Model fit								
Log Likelihood	-67,687		-66,480		-63,091		-58,842	
Pseudo-R^2	0.023		0.040		0.089		0.151	
BIC	135,451		133,059		126,454		118,284	
N	55,112		55,112		55,112		55,112	

Note. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

4.2.10 Discussion.

Mobile reviews differ from nonmobile reviews, and they are perceived differently by recipients. Study 1 shows that the peculiarities of mobile devices influence not just the use of content elements (Lurie et al., 2014) but also a reviewer's writing style. The cognitive costs of text creation on mobile devices force mobile reviewers to focus on content instead of style, such that they use fewer functions words. In line with the empirically confirmed real-time assumption, mobile reviews display higher verbal immediacy, with more personal, direct expressions about the review topic. These style elements thereby help explain why readers perceive reviews as less or more helpful, which represents a contribution to recent research on style elements in customer reviews (Ludwig et al., 2013; Schindler & Bickart, 2012). Recipients value reviews that delineate the review situation by clarifying the relationship among the content elements, using function words. In contrast, recipients discount reviews that use verbal immediate language, which appears context specific and requires prior knowledge of the reviewed topic to be unambiguous in describing the specific review situation. Whereas Lurie et al. (2014) find that content variables are rarely significant, most of the mobile-specific content characteristics in Study 1 negatively influence perceived helpfulness.

The most intriguing finding of Study 1 however is that, as in the case of Lurie et al. (2014), mobile reviews are still less valued than nonmobile reviews, even if including style-specific criteria provides a more fine-grained picture of the helpfulness of review elements. Factors beyond measurable content and style differences, as well as beyond review-, reviewer-, location-, and category-specific elements, obviously could influence recipients' perceptions of mobile reviews. The mere identification of the device used to write the review appears to offer a cue for recipients' judgments of the helpfulness of a review. Previous research on social cues suggests that people process source cues heuristically, which then influences their appraisal of communication content (Chaiken & Maheswaran, 1994; Menon &

Blount, 2003). Recipients use source cues to evaluate the helpfulness of a review, based on the similarity they recognize between their own identity and the identity of the reviewer, as disclosed by the source cue. Reviews seem valuable to recipients only if they share a similar identity with the reviewer (Forman et al., 2008; Naylor et al., 2011). Forman et al. (2008) show, for example, that reviews that disclose the geographical location of a reviewer influence product sales in that region. Naylor et al. (2011) also demonstrate that a completely anonymous review is more helpful than a review written by a reviewer who is obviously dissimilar from the recipient. Such social cues might stem not only from biographical information but also from any other information that induces comparisons between the recipient and the reviewer, including cues of the devices used. On the focal platform, only nonmobile users evaluated reviews, so the device they used to consume the review differed from the device used to generate mobile reviews. In turn, they may have discounted the helpfulness of a mobile review, due to the perceived dissimilarity between devices.

However, the field study cannot confirm whether the device tag works as a source cue. Therefore, Study 2 is a scenario based, online experiment that holds the content and style of a review constant while manipulating the device tag, to test recipients' judgments of mobile and nonmobile reviews, according to the congruency of the devices used to generate and read the review.

4.3 Study 2: Perceived Compatibility With Review Device and Causal Attributions

4.3.1 Theoretical background and hypotheses development.

Technology acceptance and innovation adoption research propose that the perceived compatibility of a technology "with the existing values, needs, and past experiences" of the adopter is an important determinant of acceptance in a technology context (G. Moore & Benbasat, 1991, p. 195). Following this view, review

recipients then might assess their similarity to the reviewer according to their perceptions of compatibility with the reviewer's device. Compatibility considerations thereby are context specific (Karahanna, Agarwal, & Angst, 2006), in the sense that recipients judge the compatibility with the reviewer's device based on their own device. This prediction is in line with the self-categorization approach in social identity theory (Turner, Oakes, Haslam, & McGarty, 1994). Even if people embrace different social identities (e.g., mobile user, nonmobile user), they use the identity that is most salient in any given situation. This self-categorization process is flexible and constructive, so the salience of an identity is highly context dependent. As in the case of the field study, recipients using a nonmobile device to read a review therefore should base their compatibility judgments on their identity as nonmobile users, which is highly salient to them in that situation. Similarly, recipients using a mobile device should self-categorize as mobile users. In turn, recipients should evaluate reviews written on a device that is congruent with their own device in the given situation as more compatible with their own values and needs than a review written on an incongruent device, which in turn prompts a better assessment of the helpfulness of the review.

> H_5: Congruence between the device used to write a review and the reading device has a positive effect on (a) perceived compatibility, which (b) improves perceived helpfulness, such that these reviews (c) have indirect positive effects on perceived helpfulness, mediated by perceived compatibility.

A question that remains though is why social cues and shared social identity increase the perceived helpfulness of customer reviews. Existing evidence of attribution behavior indicates that recipients make inferences about cause-and-effect relationships when they lack information about the specific review situation (Chen & Lurie, 2013; Sen & Lerman, 2007). They attribute information and its accuracy either internally, to reviewers and their personal disposition, or externally, to the

reviewed object (Sen & Lerman, 2007). The specific attribution path depends on the perceived level of independence between the reviewer and the review. If a recipient judges the review as detached from the specific reviewer, such that it could have been created by anyone, he or she likely attributes the motivation for the review externally, to the focus of that review (Jones & Davis, 1965; Kelley, 1973). Attribution and social identity theory both indicate that the correspondence between an observer and an actor is a good predictor of external attribution because the actor's behavior will be consistent with observers' expectations (Jones & Davis, 1965; Oakes, Turner, & Haslam, 1991). These expectations also are biased toward the self, in that observers expect their attitudes and values to be shared (Naylor et al., 2011; Ross, Greene, & House, 1977). If recipients notice that the reviewers' attitudes actually deviate from their own, they likely attribute these deviations to reviewers' personal dispositions (Ross et al., 1977).

Therefore, the perceived incompatibility of a device used to write a review with the recipient's own attitudes and values should produce an internal attribution for the review, such that it appears inconsistent or person specific. In contrast, perceived compatibility should drive external attributions because the reviewer's action (writing a review on a compatible device) is consistent with the recipient's expectations. With these distinct attributions, recipients should evaluate the helpfulness of customer reviews differently. According to attribution theory, recipients perceive messages as less helpful if they attribute them to internal dispositions rather than external stimuli (Eagly, Wood, & Chaiken, 1978). Sen and Lerman (2007) and Chen and Lurie (2013) confirm this discounting principle for customer reviews, showing that reviews attributed to the topic (i.e., product or service) are considered more helpful than reviews attributed to the reviewer. Perceived compatibility should have an indirect effect on perceived helpfulness, through the recipient's attributions.

H_6: Perceived compatibility leads the recipient to (a) attribute the reviewer's motivation externally (i.e., review subject's quality) rather than internally (i.e., reviewer's disposition), which then (b) enhances perceived helpfulness, such that this perception has (c) a positive indirect effect on perceived helpfulness, mediated by recipients' attributions.

4.3.2 Study goal and design.

To test the proposed relationship among compatibility considerations, attributions, and perceived helpfulness, this study adopts a between-subjects experimental design online, with a scenario technique and subsequent online survey. In accordance with the field study, this experiment manipulates the device the reviewer used (nonmobile vs. mobile) to assess the effect on perceptions among nonmobile and mobile recipients. To infer compatibility effects from congruent (i.e., nonmobile and nonmobile vs. mobile and mobile) and incongruent (i.e., nonmobile and mobile vs. mobile and nonmobile) dyads of review and reading devices, the experiment was run using either a nonmobile or a mobile reading device. Participants in the experiment with the nonmobile reading device were approached in a typical nonmobile situation while sitting in front of a desktop PC; participants in the experiment with a mobile reading device were contacted in a typical mobile situation while using their own smartphone in transit. In each of the reading situations, participants were randomly assigned to one of the two experimental conditions (nonmobile review device vs. mobile review device). The usability of the scenario experiment was optimized for each device without altering the content. The scenario was created in line with prior research on online customer reviews that indicates that customers that are low involved in their decision process mostly process aggregate review characteristics (e.g., average rating, average number of reviews) rather than individual review characteristics (Pan & Zhang, 2011). Hence, a situation was created where involvement is highest and therefore deep processing of the review is guaranteed. In consequence, the scenario described a situation in which the participants already had decided to meet some friends at a new Italian

pizzeria, but before going there, they checked the quality of the restaurant by reading online reviews on a customer opinion platform. Next, the scenario introduced a fictitious user who had already visited the pizzeria and wrote a review. In both conditions, the review text was the same. However, in the first condition, the review was tagged with a mobile symbol, indicating that it had been written on a mobile device. In the second condition, the review was tagged with a desktop computer symbol, indicating it had been created on a nonmobile device. The tagging mimicked the real mobile symbol used on the customer opinion platform from Study 1. A text instruction noted that the reviews had been written on either a mobile device or a desktop computer to explain the function of the tag to participants. The other review features (text, rating, user name, user's number of reviews, date of creation) remained constant.

To check that participants read the scenario and had a chance to be primed by the treatment, an instructional manipulation check (Oppenheimer, Meyvis, & Davidenko, 2009) was used both for the nonmobile and the mobile reading device. It asked participants to click on a picture in the nonmobile case or, due to technological restrictions, type in a short word in the mobile case, before clicking the continue button, which forwarded them to the online survey. If participants failed the IMC, they were excluded. Those who passed the IMC continued on to the online survey and answered questions about their perceived situational compatibility with the reviewer, attributions of the reviewer's motivation, and perceived helpfulness of the review. To ensure that participants in each condition noticed the device used to write the review, they also indicated if the review was written on a mobile or nonmobile device. The survey included control variables and a realism check, too.

Of the 754 (246) initial participants in the experiment with the nonmobile (mobile) reading device, 342 (197) passed the IMC. Subsequently, 81 (24) participants that failed the manipulation check regarding the device used to write the review were excluded. Quality checks, with regard to the speed of completion and

missing answers, excluded another 36 (8) participants. Thus, 225 (165) observations were valid and usable. Samples were pooled to assess the overall compatibility effect of congruent and incongruent devices, which resulted in a final sample of 390 participants.

In the final sample, 53.3% of all participants were male, 46.7% female. A total of 73.6% of the respondents had higher education. The majority of participants were aged between 20 and 39 years (58.7%). A total of 4.9% were younger than 20 years, 21.2% between 40 and 59, and 15.1% equal or older than 60 years. The demographic structure of the final sample therefore approximates the distribution of a typical online review platform such as Yelp (Quantcast, 2016).

4.3.3 Measures.

Device congruence is defined as 1 (= congruent) if the review device of the experimental manipulation matches with the reading device of participants and as 0 (= incongruent) otherwise. To assess the dependent variable, *perceived helpfulness*, participants rated the review on an adapted version of a helpfulness scale (Sen & Lerman, 2007; Wu, 2013) that includes four semantic differential response items (α = 0.91, composite reliability [CR] = 0.91, average variance extracted [AVE] = 0.71)[3] and uses a 7-point scale ("very useful–not at all useful," "very accurate–not at all accurate," "very informative–not informative at all," and "very helpful–not at all helpful"). The measure of the *compatibility* of the recipient with the device used by the reviewer was adapted from an innovation adoption study (G. Moore & Benbasat, 1991). Respondents in both conditions indicated whether the fact that a specific review was written on a mobile device or desktop computer (1) was compatible with their lifestyle, (2) was congruent to their own needs, and (3) fit

[3] A confirmatory factor analysis in IBM SPSS Amos 24 was used to determine composite reliabilities and average variances extracted for all multi-item measures. It also provided evidence of discriminant validity as measured by Fornell and Larcker (1981)'s criterion. The overall measurement model exhibited good fit as indicated by the respective model fit criteria (χ^2/df = 2.443, normed fit index = 0.969, confirmatory fit index = 0.981, root mean square error of approximation = 0.061).

the way they were used to dealing with such things. All items (α = 0.89, CR = 0.90, AVE = 0.74) were measured on a 7-point Likert scale (1 = “strongly disagree,” 7 = “strongly agree”). For *attributions* about the reviewer’s motives, Sen and Lerman‘s (2007) attribution measure was adopted. Respondents completed a 7-point Likert scale about the extent to which they agreed that (1) the review accurately reflected how good the pizzeria is, (2) the motive for the reviewer to write this review was to inform other customers accurately about the quality of the pizzeria, and (3) the reviewer’s evaluation was based on true experiences and feelings (α = 0.79, CR = 0.79, AVE = 0.56). Higher values imply more external attribution (reviewed subject’s quality) whereas lower values indicate internal attribution (reviewer’s disposition).

Although participants in the experiment with the mobile device (or nonmobile device) were randomly approached, one potential concern with the study design might be that predominantly users who mainly use a mobile device (or a nonmobile device respectively) in their real life took part in each of the two experiments, which would confound the results of our experimental study. Therefore, the respondents’ ratio of mobile and nonmobile Internet usage served as covariate to further control for this potential confounding effect. The ratio depicts whether participants primarily used a mobile device or nonmobile devices like desktops or laptops to go online in their everyday life. Lower scores indicated predominantly mobile Internet usage, and higher scores signaled predominantly nonmobile Internet usage. Finally, the survey collected sociodemographic variables: gender (female = 1; male = 0), age, and education (higher education = 1; lower education = 0).

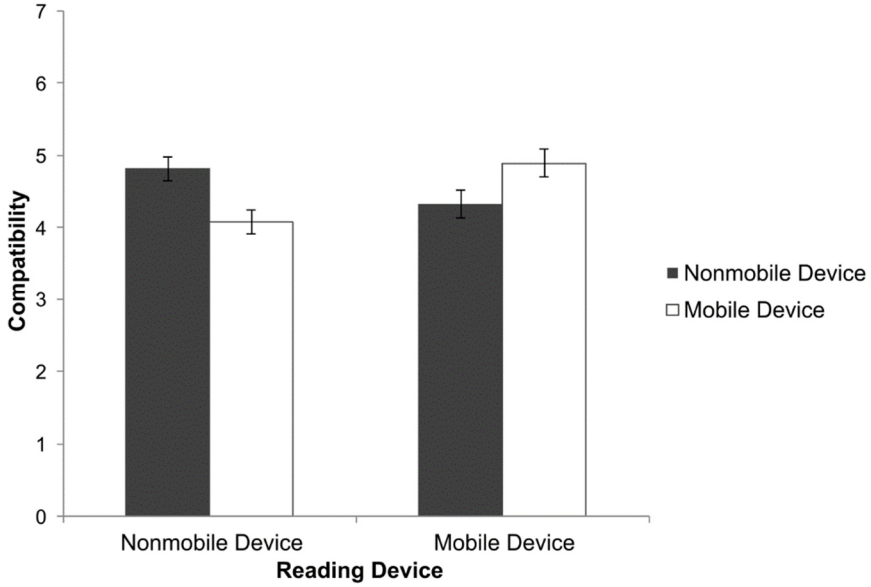
The realism check included two items (“The scenario described was realistic” and “I had no difficulty imagining myself in this situation”), with a 7-point Likert scale (Dabholkar, 1994). All the original scales were in English, but the online survey was in German, so back translation ensured their equivalence (Brislin, 1970). The correlations between the constructs were acceptable (see Table 4.3).

4.3.4 Results.

Participants considered the scenario realistic ($M_{realismitem1}$ = 5.43; $M_{realismitem2}$ = 4.87), without any significant differences between treatment groups—$t_{realismitem1,review\ device}(388) = 0.265$, $p = 0.791$, and $t_{realismitem2,review\ device}(388) = -0.443$, $p = 0.658$—or between reading devices—$t_{realismitem1,reading\ device}(387.83) = 1.540$, $p = 0.125$, and $t_{realismitem2,reading\ device}(388) = -0.326$, $p = 0.745$. The test of the proposed conceptual framework involved two separate mediation models using the PROCESS procedure (Hayes, 2013). The first mediation model included device congruence as the independent variable, compatibility with the review device as a mediator, and perceived helpfulness as the dependent variable (Hayes, 2013), along with the mobile-to-desktop usage ratio, age, gender, and education as covariates, in an attempt to test the social cue assumption (H_5). Bootstrapping with 10,000 samples provided an assessment of indirect effects (Preacher & Hayes, 2008). The results in Table 4.4 (Model I) show that device congruence has a significant direct effect on perceived compatibility, $a(I) = 0.658$, $t(384) = 4.152$, $p < 0.001$. Participants using a device for reading a review that is congruent with the device used for creating the review felt that the device used by the reviewer is more compatible with their own values and needs than participants that used an incongruent device do, in support of H_{5a}. Compatibility with the device has a significant positive effect on perceived helpfulness, $b(I) = 0.184$, $t(383) = 5.061$, $p < 0.001$; in line with H_{5b}, the more compatible a recipient feels with the reviewer's device, the more helpful the review seems. Testing for the indirect effect of the device tag on perceived helpfulness through compatibility yields a significant positive effect, $a(I) \times b(I) = 0.121$, with a 95% confidence interval (CI) of [0.059, 0.209]. As predicted by H_{5c}, compared with recipients whose device is incongruent with the reviewer's device, those who read a review on a congruent device perceive it as more helpful due to their perception of device compatibility.

To confirm that the compatibility effects are robust for both reading devices, such that nonmobile readers feel more compatible with nonmobile reviewers than with mobile reviewers, and vice versa, an interaction analysis between the review and reading device on compatibility perceptions was conducted, with the inclusion of all covariates. The writing device × reading device interaction was significant (F(1, 382) = 16.274, p < 0.001; see Figure 4.1). As planned contrasts show, when reading the review on a nonmobile device, recipients feel more compatible with the reviewer's device if it was a nonmobile device, too ($M_{nonmobile,nonmobile}$ = 4.814, $M_{nonmobile,mobile}$ = 4.084; F(1, 382) = 12.129, p < 0.01). Accordingly, when reading the review on a mobile device, recipients perceive themselves as more compatible with a mobile device used by the reviewer than with a nonmobile device ($M_{mobile,nonmobile}$ = 4.328, $M_{mobile,mobile}$ = 4.894; F(1, 382) = 5.416, p = 0.020). These results are in line with the prediction that recipients refer to the device they use in a given situation as a comparison standard for their compatibility perceptions.[4]

Figure 4.1. Compatibility as a function of review and reading device



[4] A similar analysis was conducted for helpfulness perceptions. The ANOVA yielded no significant planned contrasts for helpfulness perceptions ($M_{nonmobile,nonmobile}$ = 5.280, $M_{nonmobile,mobile}$ = 5.310; F(1, 382) = 0.026, p = 0.873; $M_{mobile,nonmobile}$ = 4.923, $M_{mobile,mobile}$ = 5.053; F(1, 382) = 0.530, p = 0.467), confirming the nonsignificant effect of device congruence on helpfulness perceptions in Table 4.4.

Table 4.3. Mean comparison and correlation of compatibility, attribution, and perceived helpfulness

	Congruent device (*N* = 193)		Incongruent device (*N* = 197)			Correlation matrix		
	Mean	*SD*	Mean	*SD*	*t*-Value	Device Congruence	Compatibility	Attribution
Compatibility	4.855	1.538	4.179	1.644	$t(388) = 4.188^{***}$	0.208***	1	
Attribution	4.511	1.205	4.560	1.202	$t(388) = -0.401$	-0.020	0.276***	1
Perceived helpfulness	5.200	1.099	5.129	1.198	$t(388) = 0.601$	-0.031	0.262***	.534***

Note. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Table 4.4. Regression coefficients, standard errors, and model summary information for (multiple) mediator models

		Model I				
		M (Compatibility)			Y (Helpfulness)	
		Coefficient	*SE*		Coefficient	*SE*
X(I) (congruent = 1, incongruent = 0)	*a*(I)	0.658***	0.159	*c'*(I)	-0.077	0.116
M(I) (Compatibility)		—	—	*b*(I)	0.184***	0.036
Constant	i_1(I)	4.345***	0.313	i_2(I)	4.769***	0.274
Covariates						
Mobile-to-desktop usage ratio		-0.135	0.081		0.011	0.058
Age		-0.136*	0.056		-0.078	0.040
Gender (male = 0, female = 1)		0.054	0.160		0.049	0.114
Education (low = 0, high = 1)		0.348	0.196		-0.233	0.140
		R^2 = 0.095			R^2 = 0.082	
		F(5, 384) = 8.016***			F(6, 383) = 5.674***	

	Effect	*SE*	*LLCI*	*ULCI*
Indirect effect of device congruence on helpfulness through compatibility (I)	0.121	0.038	0.059	0.209
Total effect of device congruence on helpfulness (I)	0.044	0.117	-0.185	0.274

		Model II				
		M(II) (Attribution)			Y(II) (Helpfulness)	
		Coefficient	*SE*		Coefficient	*SE*
X(II) (Compatibility)	*a*(II)	0.226***	0.037	*c'*(II)	0.068*	0.032
M(II) (Attribution)		—	—	*b*(II)	0.491***	0.042
Constant	i_1(II)	3.430***	0.281	i_2(II)	3.059***	0.274
Covariates						
Mobile-to-desktop usage ratio		0.003	0.060		0.008	0.050
Age		0.068	0.041		-0.109**	0.034
Gender (male = 0, female = 1)		-0.001	0.118		0.052	0.098
Education (low = 0, high = 1)		-0.178	0.145		-0.137	0.120
		R^2 = 0.093			R^2 = 0.319	
		F(5, 384) = 7.874***			F(6, 383) = 29.931***	

	Effect	*SE*	*LLCI*	*ULCI*
Indirect effect of compatibility on helpfulness through attribution (II)	0.111	0.022	0.070	0.157
Total effect of compatibility on helpfulness (II)	0.179	0.036	0.109	0.249

(Continued)

(Continued)

		Model III						
		M_1(III) (Compatibility)			M_2(III) (Attribution)			Y(III) (Helpfulness)	
		Coefficient	*SE*		Coefficient	*SE*		Coefficient	*SE*
X(III) (congruent = 1, incongruent = 0)	a_1(III)	0.658***	0.159	a_2(III)	-0.203	0.120	c'(III)	0.023	0.100
M_1(III) (Compatibility)		—	—	d_{21}(III)	0.239***	0.038	b_1(III)	0.067*	0.033
M_2(III) (Attribution)		—	—		—	—	b_2(III)	0.491***	0.043
Constant	i_{M1}(III)	4.345***	0.313	i_{M2}(III)	3.503***	0.283	i_Y(III)	3.048***	0.279
Covariates									
Mobile-to-desktop usage ratio		-0.135	0.081		0.006	0.060		0.008	0.050
Age		-0.136*	0.056		0.064**	0.041		-0.110**	0.035
Gender (male = 0, female = 1)		0.054	0.160		-0.008	0.118		0.053	0.098
Education (low = 0, high = 1)		0.348	0.196		-0.199	0.145		-0.135	0.121
		R^2 = 0.095			R^2 = 0.100			R^2 = 0.319	
		F(5, 384) = 8.016***			F(6, 383) = 7.074***			F(7, 382) = 25.599***	

	Effect	*SE*	*LLCI*	*ULCI*
Indirect effect of device congruence on helpfulness through compatibility (III)	0.044	0.026	0.003	0.106
Indirect effect of device congruence on helpfulness through compatibility and attribution in serial (III)	0.077	0.023	0.038	0.131
Indirect effect of device congruence on helpfulness through attribution (III)	-0.100	0.058	-0.221	0.007
Total effect of device congruence on helpfulness (III)	0.021	0.068	-0.117	0.150

Note. N = 390 number of bootstrap resamples = 10,000; *LLCI* = lower-level confidence interval; *ULCI* = upper-level confidence interval.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

The second mediator model (Table 4.4, Model II), with compatibility as the independent variable, attribution as a mediator, perceived helpfulness as the dependent variable, and the same covariates, tests whether attribution theory can explain why social cues and a shared social identity, as measured by compatibility perceptions, increase the perceived helpfulness of customer reviews. As proposed in H_{6a}, compatibility with the device has a significant positive effect on attribution, a(II) = 0.226, t(384) = 6.109, $p < 0.001$. A more compatible device, matching the values and needs of the recipient, leads that recipient to attribute the motivation for the review externally to the reviewed topic. Attribution has a positive effect on perceived helpfulness, b(II) = 0.491, t(383) = 11.587, $p < 0.001$, confirming H_{6b}. The more a review is attributed externally, the higher the perceived helpfulness. The indirect effect of compatibility, through attribution, on perceived helpfulness is positive and significant, a(II) × b(II) = 0.111, 95% CI [0.070, 0.157], as suggested in H_{6c}. Relative to those who feel less compatible with the reviewer's device, those who are more compatible perceive the review as more helpful, because they attribute the motivation for the review to the reviewed subject, not the reviewer.

As an additional analysis, a multiple mediator model in serial (Hayes, 2013), with device congruence as an independent variable, compatibility as a first mediator, attribution as a second mediator, perceived helpfulness as the dependent variable, and the same covariates (Table 4.4, Model III), tests for the overall effect of device congruence on perceived helpfulness. The indirect effect of device congruence on perceived helpfulness, through compatibility and attribution, is positive and significant, a_1(III) × d_{21}(III) × b_2(III) = 0.077, 95% CI [0.038, 0.131]. Relative to those who read a review on an incongruent device, those who read a review on a congruent device rate it more helpful because they feel more compatible with the

review device, which leads them to attribute the review to external reasons, involving the topic rather than the reviewer.[5]

4.3.5 Discussion.

Beyond the content and style characteristics, a simple tag that indicates the device used to write a review can serve as a source cue and influence recipients' perceptions of the review's helpfulness. By reproducing and enriching the conditions from the field study (i.e., nonmobile and mobile recipients evaluate the review helpfulness of mobile and nonmobile written reviews), this study offers evidence that the level of alignment between the device used to create the review and the device used to read it leads the recipient to perceive a review as helpful or not. Recipients using a device that is congruent with the reviewer's device value the helpfulness of reviews more because these reviews are compatible with their reading device. Thus, in both the field study and Lurie et al.'s (2014) research, the helpfulness of mobile reviews suffered discounting because recipients could only rate helpfulness on nonmobile devices. The results of the experimental study instead show that recipients using a mobile device perceive mobile, instead of nonmobile, reviews as more helpful. The findings also explain this process: When recipients feel compatible with the device used for review creation, they attribute the review's source to the quality of the reviewed subject, rather than to other reasons, such as the reviewer's personal dispositions. As indicated in previous studies (Chen & Lurie, 2013; Sen & Lerman, 2007), attributing the review to the topic is an antecedent of perceptions of a review as helpful. In summary, recipients using congruent devices perceive reviews as more helpful than recipients using incongruent devices because

[5] Again, an interaction analysis between review and reading device on attribution was conducted in order to show that the effect of device congruence on attribution behavior as suggested in Table 4.4 is the same for both reading devices. Accordingly, ANOVA yielded no significant contrasts ($M_{nonmobile,nonmobile}$ = 4.642, $M_{nonmobile,mobile}$ = 4.708; $F(1, 382) = 0.168$, $p = 0.682$; $M_{mobile,nonmobile}$ = 4.359, $M_{mobile,mobile}$ = 4.332; $F(1, 382) = 0.020$, $p = 0.887$). Furthermore, as the experiment was run on two different devices, the proposed mediation models were run separately for nonmobile and mobile participants. Results for all models yielded results that are identical in direction, strength, and significance of the proposed relationships.

they sense compatibility in their devices and thus attribute the reason for writing the review to the quality of the review subject, not to personal motivations of the reviewer.

4.4 General Discussion

4.4.1 Theoretical contributions.

The findings from this study contribute to existing research in several ways. First, this investigation represents a response to calls for empirical evidence of how technology changes the creation and reception of WOM (Berger, 2014). The findings show that the peculiarities of mobile devices invoke a specific mobile writing style, distinct from nonmobile writing styles, thereby elaborating on recent research that notes the influential role of the communication channel on WOM content (Berger & Iyengar, 2013). By testing the content and style characteristics of customer reviews on a multicategory customer opinion platform, the present study also extends and validates evidence provided by Lurie et al. (2014) who analyzed data from a single category platform featuring restaurant reviews only. Mobile-specific linguistic characteristics, such as shorter length, fewer function words, and more verbal immediacy, make customer reviews appear less helpful to recipients. In addition, the simple knowledge of what kind of device the reviewer used to create the review influences recipients' judgments of the review's helpfulness, depending on whether the devices align. The evidence of this mobile effect, in both field and experimental studies, helps confirm Lurie et al.'s (2014) findings. In extending prior mobile device research that has focused primarily on what motivates consumers to use mobile devices for their WOM behavior (Okazaki, 2008; Palka et al., 2009), the current findings add insights into how mobile devices used by consumers for WOM influence the perceptions of communication partners.

Second, this study elaborates on previous research into the role of source cues. The current findings indicate that recipients use device tags to infer

information about the reviewer and compare their identities. This finding is particularly noteworthy because devices offer weak social identifiers; they do not reflect personal dispositions or entrenched background traits (Forman et al., 2008; Naylor et al., 2011). However, it resonates with the minimal group paradigm of social identity theory, in that minimal, seemingly meaningless information is all that is needed to trigger social identification processes (Billig & Tajfel, 1973). By integrating social identity and attribution theory, this study also helps explain why a shared social identity enhances the perceived helpfulness of a review. Previous conceptualizations have not differentiated the perceptional process of similarity from an attributional process, though these cognitive processes are analytically distinct (Racherla, Mandviwalla, & Connolly, 2012). The current findings indicate that recipients first evaluate their perceived compatibility with the reviewer, in terms of the devices used, and then, on the basis of compatibility considerations, attribute the motive for the review to either personal aspects of the reviewer or the subject of the review.

Third, as an extension of the effect of perceived compatibility on technology and innovation usage (Kleijnen et al., 2007; G. Moore & Benbasat, 1991), this study shows that the perceived compatibility of the recipient with the reviewer, according to the devices they use, is critical to appraisals of the review. People assess their compatibility with a technology when evaluating whether to use it but also exhibit compatibility considerations in communication situations in which both the sender and receiver use technologies. Recipients evaluate the technology usage of their communication partner to make social inferences and judge the credibility of the content. Furthermore, the reference point for assessing compatibility depends not on the personal dispositions of the recipient but on the technology the recipient uses to access that content. This finding expands Karahanna et al.‘s (2006, p. 784) finding that compatibility considerations are driven by “reality as it is currently experienced.” Such findings are particularly valuable in omni-channel retail settings, with their

blurred channel borders that force consumers to address different technologies during single retail experiences (Verhoef, Kannan, & Inman, 2015).

Fourth, this study contributes to research on review helpfulness by introducing two style characteristics that influence the helpfulness of a customer review. Function words and verbal immediacy increase the diagnosticity of reviews by providing additional information about the relationship of the reviewer with the reviewed topic and the review situation, which are not solely conveyed by content elements. Function words contextualize content elements and therefore increase readability and the ability to understand complex relationships (Hartley et al., 2003). Verbal immediacy signals high attachment and involvement (Borelli et al., 2011; Mehrabian, 1967), which causes the review to appear biased or subjective and less helpful. These two style characteristics thus provide a more fine-grained picture of the impact of content and style criteria on perceived helpfulness (Lurie et al., 2014; Schindler & Bickart, 2012; Scholz & Dorner, 2013).

4.4.2 Managerial implications.

Providing helpful content to customers is elementary for review platforms; reviews constitute their core value proposition. Only if reviews help customers in their purchase decision processes customers will make continuous use of the platform. The number of customers simultaneously influences the attractiveness of the review platform for future customers and for advertisers because platforms operate within multisided markets with network externalities (Rochet & Tirole, 2006). Furthermore, prior research suggests that review characteristics, such as source cues or linguistic style, influence not only helpfulness perceptions but also sales of the listed items (Forman et al., 2008; Ludwig et al., 2013). The impact on sales is a particularly valuable finding for review platforms that generate revenues by charging fees for transactions between each listed firm and customers or click-through rates

by customers. The present study suggests two major ways to improve the helpfulness of customer reviews and, thus, platform sales.

First, platforms should take caution before tagging content as mobile or nonmobile. Popular review platforms such as TripAdvisor or Booking.com use those device tags, especially for mobile-written reviews, to promote their mobile applications or disclose the context of the specific review situation (Seave, 2013). Yet the results of the present study suggest that such practices can create a boomerang effect if recipients use a device that is distinct from the device used by the reviewer. To avoid this device effect, the platform might avoid any device tags because not disclosing identity-related information about the reviewer is better, in terms of persuasion, than disclosing an identity that is dissimilar. In this case, anonymous reviews perform just as well as reviews that disclose a similar identity (Naylor et al., 2011). Should firms want to apply a device tag, they should use a dynamic sorting mechanism that displays reviews according to the recipients' devices, rather than sorting reviews as a function of recency. Thus, nonmobile reviews would be first if recipients use nonmobile devices, whereas mobile-written reviews should come first if recipients use a mobile device. Both options imply, however, that firms cannot use the device tag to promote their mobile application because nonmobile users cannot be confronted with the mobile tag anymore. Managers thus should consider new approaches to increase the adoption of mobile devices among their customers, such as offering redeemable coupons for reviews through mobile applications.

Second, platform managers must acknowledge that mobile reviews differ from nonmobile reviews in terms of their content- and style-specific characteristics, such that the content- and style-specific peculiarities of mobile reviews (e.g., fewer words, more affective content) are generally perceived as less helpful. Therefore, platform managers might add systems or guidelines to improve the linguistic quality of mobile reviews (Scholz & Dorner, 2013). Any such guidelines would need to

account for the challenges of creating content with mobile devices, including the cognitive costs imposed by small screens and tiny keyboards. The test of the real-time assumption also reveals that a majority of mobile-created reviews are written during or shortly after the product or service experience. Thus, firms should consider the constraints of the real-time situation in which mobile reviews are usually written. Both aspects might limit the possibilities for encouraging more quality, such that review platforms need to develop easy-to-use systems through innovative solutions (e.g., voice commands, auto-completion to increase the number of content and function words).

4.4.3 Limitations and further research.

Several limitations of this study suggest avenues for further research. First, the experimental study focused on the effect of the device tag on perceived helpfulness by isolating a single review and holding all other factors constant. However, review valance (Chen & Lurie, 2013), product type (Sen & Lerman, 2007), or even the linguistic characteristics of the review itself can all moderate attributional processes. Further research should include these factors in a broader experimental design, to investigate specifically whether these factors moderate attribution behavior after recipients assess their compatibility with the reviewer's device or already influence those compatibility considerations about the reviewer. Such an investigation could clarify situations in which recipients consider source cues in their evaluation process. Do recipients use source cues simultaneously with the review's informational content to judge the helpfulness of a review, as proposed by the theory of heuristic cues (Chaiken & Maheswaran, 1994)? Or do they consider only source cues that challenge the credibility of the informational content? For example, recipients might assess their compatibility with the reviewer's device only after reading a positive review that they perceive as subjectively biased (Sen & Lerman, 2007).

Second, the field study is based on data from a single review platform. Although this platform contains a multitude of categories and was one of the most popular platforms in Europe before its acquisition, validating the differences in the content and style of mobile reviews with data from other review platforms would be a useful extension. In such extensions, researchers could investigate the information provided by pictures; in the present study context, no information about pictures was available during the data collection period. However, images increase the usability of online reviews (Cheng & Ho, 2015), and mobile devices make it easy for reviewers to take pictures of the service experience during their consumption. Therefore, supplementing mobile customer reviews with images might increase the perceived helpfulness of mobile reviews and attenuate the negative effects of their text-specific characteristics, in terms of content and style. This mobile-specific feature should be considered in further research.

Third, by including verbal immediacy in the analysis of mobile reviews, the authors attempt to capture some context-specific effects of the mobile review situation. However, mobile behavior is very context specific, so further research might try to control other factors in the situational context. For example, do reviewers write during or after the consumption experience? Do they generate reviews while in transit, at home, or in the office? The reception of communication content on mobile devices also might vary across contexts (Grewal, Bart, Spann, & Zubcsek, 2016). How do perceptions of reviews (and tagging) change if recipients are not in motion but at home or at work (Luo, Andrews, Fang, & Phang, 2014)? Does the degree of crowdedness also influence review evaluations (Andrews, Luo, Fang, & Ghose, 2016)? Gaining further insights into the influence of context, for both creating and reading reviews, might be valuable.

4.5 Conclusion

Sharing consumption experiences in real time with the help of mobile devices has more negative than positive effects on the appraisals of these reviews by other consumers—at least if they are not using a mobile device. Using field data, the authors demonstrate that beyond the content of a review, recipients discount the style in which mobile reviews are written. Even when controlling for style- and content-specific differences, the simple fact that a review was identified as written on a mobile device negatively influences the helpfulness of that review. By elaborating on this mobile effect in a scenario experiment, the authors also provide evidence that recipients assess their compatibility with the reviewer's device, based on a simple device tag. Only if this device is congruent with the device that recipients use to read a review do they feel compatible and judge the review as helpful because it can be attributed to the quality of the review subject. However, if recipients feel incompatible, because of differences in the devices used, they attribute the review to the personal dispositions of the reviewer and discount its helpfulness. These results thus challenge the common industry practice of tagging content according to how it was created, which induces a boomerang effect when recipients sense incompatibility with reviewers' devices.

4.6 References

Andrews, M., Luo, X., Fang, Z., & Ghose, A. (2016). Mobile ad effectiveness: Hyper-contextual targeting with crowdedness. *Marketing Science*, *35*, 218–233. https://doi.org/10.1287/mksc.2015.0905

Balasubramanian, S., Peterson, R. A., & Jarvenpaa, S. L. (2002). Exploring the implications of m-commerce for markets and marketing. *Journal of the Academy of Marketing Science*, *30*, 348–361. https://doi.org/10.1177/009207002236910

Barasch, A., & Berger, J. (2014). Broadcasting and narrowcasting: How audience size affects what people share. *Journal of Marketing Research*, *51*, 286–299. https://doi.org/10.1509/jmr.13.0238

Bazarova, N. N., Taft, J. G., Choi, Y. H., & Cosley, D. (2012). Managing impressions and relationships on Facebook: Self-presentational and relational concerns revealed through the analysis of language style. *Journal of Language and Social Psychology*, *32*, 121–141. https://doi.org/10.1177/0261927X12456384

Berger, J. (2014). Word of mouth and interpersonal communication: A review and directions for future research. *Journal of Consumer Psychology*, *24*, 586–607. https://doi.org/10.1016/j.jcps.2014.05.002

Berger, J., & Iyengar, R. (2013). Communication channels and word of mouth: How the medium shapes the message. *Journal of Consumer Research*, *40*, 567–579. https://doi.org/10.1086/671345

Billig, M., & Tajfel, H. (1973). Social categorization and similarity in intergroup behaviour. *European Journal of Social Psychology*, *3*, 27–52. https://doi.org/10.1002/ejsp.2420030103

Borelli, J. L., Sbarra, D. A., Mehl, Matthias, & David, D. H. (2011). Experiential connectedness in children's attachment interviews: An examination of natural word use. *Personal Relationships*, *18*, 341–351. https://doi.org/10.1111/j.1475-6811.2010.01294.x

Bradac, J. J., Bowers, J. W., & Courtright, J. A. (1979). Three language variables in communication research: Intensity, immediacy, and diversity. *Human Communication Research*, *5*, 257–269. https://doi.org/10.1111/j.1468-2958.1979.tb00639.x

Chaiken, S., & Maheswaran, D. (1994). Heuristic processing can bias systematic processing: Effects of source credibility, argument ambiguity, and task importance on attitude judgment. *Journal of Personality and Social Psychology*, *66*, 460–473. https://doi.org/10.1037/0022-3514.66.3.460

Chen, Z., & Lurie, N. H. (2013). Temporal contiguity and negativity bias in the impact of online word of mouth. *Journal of Marketing Research*, *50*, 463–476. https://doi.org/10.1509/jmr.12.0063

Cheng, Y.-H., & Ho, H.-Y. (2015). Social influence's impact on reader perceptions of online reviews. *Journal of Business Research*, *68*, 883–887. https://doi.org/10.1016/j.jbusres.2014.11.046

Chung, C., & Pennebaker, J. W. (2007). The psychological functions of function words. In K. Fiedler (Ed.), *Social communication* (pp. 343–359). New York, NY: Psychology Press. https://doi.org/10.4324/9780203837702

Dabholkar, P. A. (1994). Incorporating choice into an attitudinal framework: Analyzing models of mental comparison processes. *Journal of Consumer Research*, *21*, 100–118. https://doi.org/10.1086/209385

Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management Science*, *32*, 554–571. https://doi.org/10.1287/mnsc.32.5.554

Daft, R. L., & Macintosh, N. B. (1981). A tentative exploration into the amount and equivocality of information processing in organizational work units. *Administrative Science Quarterly*, *26*, 207–224. https://doi.org/10.2307/2392469

Eagly, A. H., Wood, W., & Chaiken, S. (1978). Causal inferences about communicators and their effect on opinion change. *Journal of Personality and Social Psychology*, *36*, 424–435. https://doi.org/10.1037/0022-3514.36.4.424

Forman, C., Ghose, A., & Wiesenfeld, B. (2008). Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. *Information Systems Research*, *19*, 291–313. https://doi.org/10.1287/isre.1080.0193

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*, 39–50. https://doi.org/10.2307/3151312

Graesser, A. C., McNamara, D. S., Louwerse, M. M., & Cai, Z. (2004). Coh-Metrix: Analysis of text on cohesion and language. *Behavior Research Methods, Instruments, & Computers*, *36*, 193–202. https://doi.org/10.3758/BF03195564

Greene, W. H. (2012). *Econometric analysis* (7th international ed.). Boston, MA: Pearson.

Grewal, D., Bart, Y., Spann, M., & Zubcsek, P. P. (2016). Mobile advertising: A framework and research agenda. *Journal of Interactive Marketing*, *34*, 3–14. https://doi.org/10.1016/j.intmar.2016.03.003

Grinter, R., & Eldridge, M. (2003). Wan2tlk?: everyday text messaging. In *CHI '03 proceedings of the SIGCHI conference on human factors in computing systems* (pp. 441–448). https://doi.org/10.1145/642611.642688

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis* (7th international ed.). Harlow, UK: Pearson.

Hartley, J., Pennebaker, J. W., & Fox, C. (2003). Abstracts, introductions and discussions: How far do they differ in style? *Scientometrics*, *57*, 389–398. https://doi.org/10.1023/A:1025008802657

Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. *Methodology in the social sciences*. New York, NY: Guilford Press.

Hennig-Thurau, T., Malthouse, E. C., Friege, C., Gensler, S., Lobschat, L., Rangaswamy, A., & Skiera, B. (2010). The impact of new media on customer relationships. *Journal of Service Research*, *13*, 311–330. https://doi.org/10.1177/1094670510375460

Ireland, M. E., & Pennebaker, J. W. (2010). Language style matching in writing: Synchrony in essays, correspondence, and poetry. *Journal of Personality and Social Psychology*, *99*, 549–571. https://doi.org/10.1037/a0020386

Jiang, Z., & Benbasat, I. (2004). Virtual product experience: Effects of visual and functional control of products on perceived diagnosticity and flow in electronic shopping. *Journal of Management Information Systems*, *21*, 111–147. https://doi.org/10.1080/07421222.2004.11045817

Jones, E. E., & Davis, K. E. (1965). From acts to dispositions. The attribution process in person perception. In L. Berkowitz (Ed.), *Advances in experimental social psychology* (Volume 2, pp. 219–266). New York, NY: Academic Press.

Karahanna, E., Agarwal, R., & Angst, C. M. (2006). Reconceptualizing compatibility beliefs in technology acceptance research. *MIS Quarterly*, *30*, 781–804. https://doi.org/10.2307/25148754

Kelley, H. H. (1973). The processes of causal attribution. *American Psychologist*, *28*, 107–128. https://doi.org/10.1037/h0034225

Kleijnen, M., de Ruyter, K., & Wetzels, M. (2007). An assessment of value creation in mobile service delivery and the moderating role of time consciousness. *Journal of Retailing*, *83*, 33–46. https://doi.org/10.1016/j.jretai.2006.10.004

Ling, R., & Baron, N. S. (2007). Text messaging and IM: Linguistic comparison of American college data. *Journal of Language and Social Psychology*, *26*, 291–298. https://doi.org/10.1177/0261927X06303480

Ludwig, S., de Ruyter, K., Friedman, M., Brüggen, E. C., Wetzels, M., & Pfann, G. (2013). More than words: The influence of affective content and linguistic style matches in online reviews on conversion rates. *Journal of Marketing*, *77*, 87–103. https://doi.org/10.1509/jm.11.0560

Luo, X., Andrews, M., Fang, Z., & Phang, C. W. (2014). Mobile targeting. *Management Science*, *60*, 1738–1756. https://doi.org/10.1287/mnsc.2013.1836

Lurie, N. H., Ransbotham, S., & Liu, H. (2014). *The characteristics and perceived value of mobile word of mouth* (Marketing Science Institute Working Paper Series No. 14). Retrieved from http://www.msi.org/reports/the-characteristics-and-perceived-value-of-mobile-word-of-mouth/

McNamara, D. S., Kintsch, E., Songer, N. B., & Kintsch, W. (1996). Are good texts always better? Interactions of text coherence, background knowledge, and levels of understanding in learning from text. *Cognition and Instruction*, *14*, 1–43. https://doi.org/10.1207/s1532690xci1401_1

Mehrabian, A. (1967). Attitudes inferred from non-immediacy of verbal communications. *Journal of Verbal Learning and Verbal Behavior*, *6*, 294–295. https://doi.org/10.1016/S0022-5371(67)80113-0

Mehrabian, A. (1968). The effect of context on judgments of speaker attitude. *Journal of Personality*, *36*, 21–32. https://doi.org/10.1111/j.1467-6494.1968.tb01457.x

Menon, T., & Blount, S. (2003). The messenger bias: A relational model of knowledge valuation. *Research in Organizational Behavior*, *25*, 137–186. https://doi.org/10.1016/S0191-3085(03)25004-8

Moore, G., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, *2*, 192–222. https://doi.org/10.1287/isre.2.3.192

Moore, S. (2015). Attitude predictability and helpfulness in online reviews: The role of explained actions and reactions. *Journal of Consumer Research*, *42*, 30–44. https://doi.org/10.1093/jcr/ucv003

Mudambi, S. M., & Schuff, D. (2010). What makes a helpful online review? A study of customer reviews on amazon.com. *MIS Quarterly*, *34*, 185–200. https://doi.org/10.2307/20721420

Naylor, R. W., Lamberton, C. P., & Norton, D. A. (2011). Seeing ourselves in others: Reviewer ambiguity, egocentric anchoring, and persuasion. *Journal of Marketing Research*, *48*, 617–631. https://doi.org/10.1509/jmkr.48.3.617

Niederhoffer, K. G., & Pennebaker, J. W. (2002). Linguistic style matching in social interaction. *Journal of Language and Social Psychology*, *21*, 337–360. https://doi.org/10.1177/026192702237953

Nielsen. (2013). *The mobile consumer. A global snapshot*. Retrieved from http://www.nielsen.com/content/dam/corporate/uk/en/documents/Mobile-Consumer-Report-2013.pdf

Oakes, P. J., Turner, J. C., & Haslam, S. A. (1991). Perceiving people as group members: The role of fit in the salience of social categorizations. *British Journal of Social Psychology*, *30*, 125–144. https://doi.org/10.1111/j.2044-8309.1991.tb00930.x

Okazaki, S. (2008). Determinant factors of mobile-based word-of-mouth campaign referral among Japanese adolescents. *Psychology & Marketing*, *25*, 714–731. https://doi.org/10.1002/mar.20235

Okazaki, S., & Mendez, F. (2013). Perceived ubiquity in mobile services. *Journal of Interactive Marketing*, *27*, 98–111. https://doi.org/10.1016/j.intmar.2012.10.001

Oppenheimer, D. M., Meyvis, T., & Davidenko, N. (2009). Instructional manipulation checks: Detecting satisficing to increase statistical power. *Journal of Experimental Social Psychology*, *45*, 867–872. https://doi.org/10.1016/j.jesp.2009.03.009

Palka, W., Pousttchi, K., & Wiedemann, D. G. (2009). Mobile word-of-mouth – A grounded theory of mobile viral marketing. *Journal of Information Technology*, *24*, 172–185. https://doi.org/10.1057/jit.2008.37

Pan, Y., & Zhang, J. (2011). Born unequal: A study of the helpfulness of user-generated product reviews. *Journal of Retailing*, *87*, 598–612. https://doi.org/10.1016/j.jretai.2011.05.002

Pennebaker, J. W., Booth, R. J., & Francis, M. E. (2007). LIWC2007: Linguistic inquiry and word count. Austin, Texas. Retrieved from http://www.liwc.net/

Pennebaker, J. W., & King, L. A. (1999). Linguistic styles: Language use as an individual difference. *Journal of Personality and Social Psychology*, *77*, 1296–1312. https://doi.org/10.1037/0022-3514.77.6.1296

Pennebaker, J. W., Mehl, Matthias, & Niederhoffer, K. G. (2003). Psychological aspects of natural language use: Our words, our selves. *Annual Review of Psychology*, *54*, 547–577. https://doi.org/10.1146/annurev.psych.54.101601.145041

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*, 879–891. https://doi.org/10.3758/BRM.40.3.879

Quantcast. (2016). yelp.com. Retrieved from https://www.quantcast.com/yelp.com?country=DE#trafficCard

Racherla, P., Mandviwalla, M., & Connolly, D. J. (2012). Factors affecting consumers' trust in online product reviews. *Journal of Consumer Behaviour*, *11*, 94–104. https://doi.org/10.1002/cb.385

Rochet, J.-C., & Tirole, J. (2006). Two-sided markets: A progress report. *The RAND Journal of Economics*, *37*, 645–667. https://doi.org/10.1111/j.1756-2171.2006.tb00036.x

Ross, L., Greene, D., & House, P. (1977). The "false consensus effect": An egocentric bias in social perception and attribution processes. *Journal of Experimental Social Psychology*, *13*, 279–301. https://doi.org/10.1016/0022-1031(77)90049-X

Schindler, R. M., & Bickart, B. (2012). Perceived helpfulness of online consumer reviews: The role of message content and style. *Journal of Consumer Behaviour*, *11*, 234–243. https://doi.org/10.1002/cb.1372

Scholz, M., & Dorner, V. (2013). The recipe for the perfect review? An investigation into the determinants of review helpfulness. *Business and Information Systems Engineering*, *5*, 141–151. https://doi.org/10.1007/s12599-013-0259-3

Seave, A. (2013). How TripAdvisor grows scale and network effects: Expertise in gathering UGC. Retrieved from https://www.forbes.com/sites/avaseave/2013/06/20/how-tripadvisor-grows-scale-and-network-effects-expertise-in-gathering-ugc/#1fd5dc2c50ef

Sen, S., & Lerman, D. (2007). Why are you telling me this? An examination into negative consumer reviews on the web. *Journal of Interactive Marketing*, *21*, 76–94. https://doi.org/10.1002/dir.20090

Shankar, V., Venkatesh, A., Hofacker, C. F., & Naik, P. (2010). Mobile marketing in the retailing environment: Current insights and future research avenues. *Journal of Interactive Marketing*, *24*, 111–120. https://doi.org/10.1016/j.intmar.2010.02.006

Tang, C., & Guo, L. (2015). Digging for gold with a simple tool: Validating text mining in studying electronic word-of-mouth (eWOM) communication. *Marketing Letters*, *26*, 67–80. https://doi.org/10.1007/s11002-013-9268-8

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology*, *29*, 24–54. https://doi.org/10.1177/0261927X09351676

Turner, J. C., Oakes, P. J., Haslam, S. A., & McGarty, C. (1994). Self and collective: Cognition and social context. *Personality and Social Psychology Bulletin*, *20*, 454–463. https://doi.org/10.1177/0146167294205002

Verhoef, P. C., Kannan, P. K., & Inman, J. J. (2015). From multi-channel retailing to omni-channel retailing. Introduction to the special issue on multi-channel retailing. *Journal of Retailing*, *91*, 174–181. https://doi.org/10.1016/j.jretai.2015.02.005

Wiener, M., & Mehrabian, A. (1968). *Language within language: Immediacy, a channel in verbal communication*. New York, NY: Appleton-Century-Crofts.

Wolf, M., Horn, A. B., Mehl, Matthias R., Haug, S., Pennebaker, J. W., & Kordy, H. (2008). Computergestützte quantitative Textanalyse. Äquivalenz und Robustheit der deutschen Version des Linguistic Inquiry and Word Count. *Diagnostica*, *54*, 85–98. https://doi.org/10.1026/0012-1924.54.2.85

Wu, P. F. (2013). In search of negativity bias: An empirical study of perceived helpfulness of online reviews. *Psychology & Marketing*, *30*, 971–984. https://doi.org/10.1002/mar.20660

Yao, B., Yuan, H., Qian, Y., & Xu, X. (2016). Exploring the local effects of helpful reviews on online product sales. 2016 13th International Conference on Service Systems and Service Management (ICSSSM).

Zhu, F., & Zhang, X. (2010). Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of Marketing*, *74*, 133–148. https://doi.org/10.1509/jmkg.74.2.133

5. Study 4: Born Free?! How Prior Strategic Commitments Influence Customer Orientation Behaviors and Their Outcomes in Free E-Services

Sebastian Schubach, Nicole J. Heß, Jan H. Schumann, Eva M. Anderl, Armin März

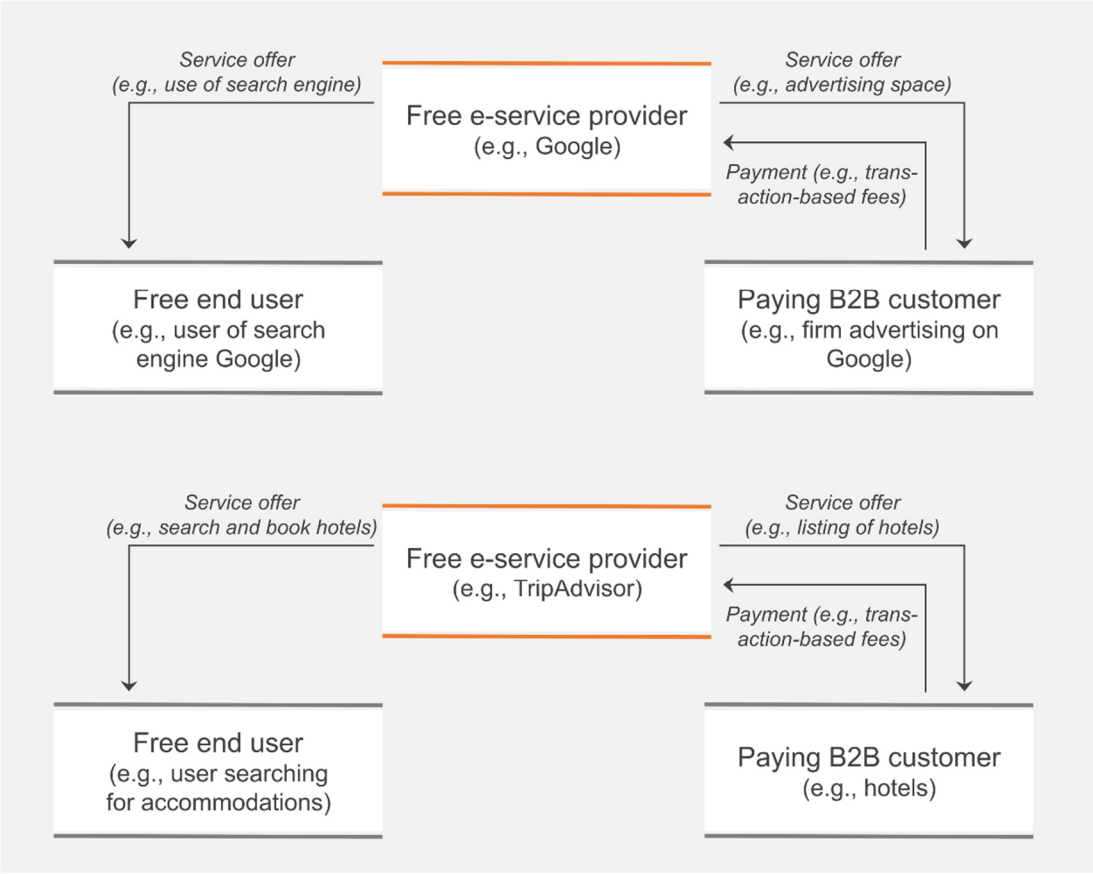
Revising for Second Review at *Journal of Service Research* (VHB Ranking: A)

Research on customer orientation, i.e., a firm's understanding of one's target buyers to be able to create superior value, has predominantly focused on dyadic customer-firm-relationships. Yet, the increasing prevalence of free e-services requires further research that extends this dyadic perspective. Free e-services are two-sided markets where e-service providers offer services for free to end users while paying B2B customers (e.g., advertisers) cross-subsidize these free offers. In one qualitative and one quantitative study, the authors demonstrate that free e-service providers possess different mental models about how free e-services work and that they therefore differ in customer orientation behaviors and outcomes. Free-born providers, that from the outset strategically committed themselves to the free business model, developed a mental model of free e-services that matches their particularities (i.e., superiority of free end users, interdependencies between both populations). They use customer orientation toward one customer population to increase the satisfaction of this population and the other simultaneously and, thus, are reaching their financial goals. Laggards, that started with a non-free business model before launching their free e-service, however, cannot exploit the full potential of their customer orientation behaviors, as they lack to acknowledge the superiority of free end users. The findings offer new theoretical insights for research and provide managers with actionable implications.

5.1 Introduction

Extant marketing research has shown that with customer orientation, i.e., a company's "sufficient understanding of one's target buyers to be able to create superior value" (Narver & Slater, 1990, p. 21), firms can increase customer satisfaction and achieve a substantial competitive advantage. Customer orientation research thus far has mainly focused on customer orientation in dyadic customer-firm-relationships, where firms serve the needs of only one customer population. Such research has investigated drivers of customer orientation, its outcomes, and contingency factors (Jaworski & Kohli, 1993; Kirca, Jayachandran, & Bearden, 2005; Narver & Slater, 1990). Yet, in the new economy, two- or even multi-sided markets have evolved where firms have to serve the needs of more than one customer population. In these two- or multi-sided markets, firms bring together multiple distinct customer populations who interact with one another. Free e-services, such as Google or TripAdvisor, are the most successful manifestations of such multi-sided markets. As Figure 5.1 illustrates, those firms offer an electronic service for free to one customer population (i.e., free end users). As such, free end users can use Google's search engine for free or search for accomodations and book them on TripAdvisor. To finance this free offering, free e-service providers enable a second customer population (i.e., paying B2B customers) to interact with free end users, for instance through advertising (Google) or through listing products and services (TripAdvisor) on the providers's platform in exchange for a fee. In this respect, we explicitly exclude freemium models from our study as freemium models entail only one customer population that is segmented according to end users' willingness to pay. Furthermore, freemium models commonly lack an interaction between different customer populations, which lies at the heart of the definition of two-sided markets (Eisenmann, Parker, & van Alstyne, 2006).

Figure 5.1. Illustration of Google's and TripAdvisor's business model



However, not all providers are as successful as Google or TripAdvisor. Especially publishing houses have difficulties with this free business model and are constantly searching for ways to convert free end users into paying ones (The Economist, 2015). One reason for this obvious heterogeneity can be rooted in different mental models of free e-services, i.e., knowledge structures about how free e-services work (Gary & Wood, 2011) which influnece customer orientation behaviors. Firms like Google or TripAdvisor started their business around the free business model and therefore were able to learn about free e-services' particularities from the beginning on. In contrast, publishing houses, were not used to end consumers not paying for a product or service offer when launching a free e-service. Thus, publishing houses' knowledge structures about free e-services might be influenced by their prior experiences in markets without free end consumers.

So far, there is only one study investigating customer orientation in settings with more than one customer population. Chakravarty, Kumar, and Grewal (2014) analyzed B2B-platforms with two paying customer populations and found evidence that firms are customer oriented toward each population in two-sided market settings. Through customer orientation toward one customer population, platforms can either increase the platform's total customer orientation, or prioritize one customer population over the other. Whereas the authors extend customer orientation research by emphasizing that customer orientation toward more than one customer population is mandatory for a platform's success, their study lacks to address the specific challenges of free e-services. Research has shown that providers must acknowledge the importance of free end users for free e-services' success, even if they do not provide monetary proceeds. Free end users are even more important than paying B2B customers (Gupta & Mela, 2008; Kraemer, Hinz, & Skiera, 2010). Moreover, these studies have shown that free end users and paying B2B customers are not independent of each other, in that marketing actions directed at one customer population also affect the other, and vice versa.

The present study aims to expand current knowledge on customer orientation in multi-sided markets with two studies. In a first exploratory study (Study 1), we assess providers' mental models of free e-services and of how customer orientation works in this setting. Based on providers' mental models we investigate the outcome effects of customer orientation in free e-services in a quantitative study (Study 2). Due to the interdependencies that govern free e-services, our specific interest is how customer orientation toward one population affects the satisfaction of the other population, and vice versa. Besides investigating the effects on customer satisfaction, we further analyze how the different customer orientations directly contribute to the providers' financial goal attainment.

Both studies reveal that providers differ considerably in their mental models of free e-services and in their subsequent customer orientation behaviors,

depending on the nature of their strategic commitment to the free business model. Providers that committed themselves to the free business model from the outset (i.e., free-borns), are aware of free end users' superiority and the interdependency of free end users and paying B2B customers. For this reason, they take into account the effect of their customer orientation behavior toward one customer population on the other population's satisfaction, and vice versa. Thus, they can increase the satisfaction of both customer populations simultaneously, even while they are customer oriented to one population only. In contrast, providers that did not commit themselves to the free business model from the beginning (i.e., laggards), less acknowledge how critical free end users are for free e-services, and overestimate the importance of paying B2B customers. Such providers are customer oriented toward free end users to the same degree as free-born firms are. However, they do not prioritize free end users over paying B2B customers in their customer orientation behaviors and loose track of end users' needs when they are customer oriented toward paying B2B customers. As such, they do not bear in mind the impact their customer orientation behavior toward paying B2B customers has on free end users' satisfaction, and thus, are not able to increase both, the satisfaction of free end users and of paying B2B customers simultaneously. In addition, our results reveal that laggards' customer orientation behavior toward free end users and paying B2B customers is less efficient and effective than that of free-borns. With these rsults, our study makes several theoretical contributions to research on customer orientation and two-sided markets.

Our contributions to research on customer orientation are three-fold: First, our findings expand existing knowledge of customer orientation in two-sided markets by disaggregating a platform's customer orientation into its individual parts. Second, we show customer orientation to be necessary for a firm's financial success, even toward customer populations that do not provide any monetary value, as long as they interact with paying instances. Third, we disclose that a firm's prior strategic

commitment influences customer orientation behavior and outcomes through different mental models.

Additionally, we contribute to research on two-sided markets. First we add meaningful insights to extant research by identifying customer orientation as an appropriate coordination strategy to meet the expectations of multiple market sides and, hence, to gain their commitment to the platform. Second, we show that the level of customer orientation behavior toward free end users is higher than toward paying B2B customers, even if free end users do not provide any monetary value. Third, we unearth new strategies for laggards to accommodate free businesses.

Moreover, our results provide valuable and actionable implications for providers of free e-services. Providers need to be customer oriented toward both, free end users and paying B2B customers, even if the former provide no monetary value in exchange for the service offer. Apart from just fulfilling the needs of each customer population, providers should leverage the interdependency of free end users and paying B2B customers by considering how customer orientation toward one of the two populations affects the other. Further, by acknowledging the superiority of free end users, customer orientation behavior toward free end users and paying B2B customers can yield additional financial benefits. Those results are especially important for laggards that espoused a non-free business model prior to launching a free e-service.

The remainder of this article is organized as follows: After a brief overview of prior research on customer orientation and free e-services, we report on the qualitative study (Study 1) and its results. The findings of Study 1, together with evidences from prior research, provide the conceptual foundation for our quantitative, survey-based study (Study 2) among free e-service providers. Finally, we discuss the results and the implications for research and practice.

5.2 Theoretical Background

Research in the field of customer orientation thus far mainly focusses on so called pipeline firms (van Alstyne, Parker, & Choudary, 2016), which have to serve the needs of one customer population only. In this context, Narver and Slater (1990) show that customer orientation positively impacts firm performance. Numerous follow-up studies confirm this positive relationship between customer orientation and firm performance (Jaworski & Kohli, 1993; Kirca et al., 2005). One explanation for customer orientation positively impacting firm performance is rooted in customer satisfaction, which is achieved by fulfillment, but also overfulfillment of customer expectations and needs. Customer satisfaction, in turn, positively translates into firm success (E. Anderson & Sullivan, 1993; Brady & Cronin, 2001; Slater & Narver, 1994).

However, customer orientation in multi-sided markets is an area that is ripe for additional research, as studies in this area are still rather limited. Only one recent study by Chakravarty et al. (2014) provides evidence that customer orientation is a valuable tool for the success of platform firms. By means of B2B-platforms the authors have confirmed that these online platforms hold separate customer orientations toward the distinct customer populations. According to Chakravarty et al. (2014), the sum of the separate customer orientations represents the total customer orientation of a platform, which in turn, positively impacts a platform's competitive advantage. Customer orientation asymmetry, in contrast, represents the difference between the separate customer orientations and reflects the prioritization of one customer population over the other. Customer orientation asymmetry enables counterbalancing dependency on one customer population and, thus, increases a platform's performance.

Whereas Chakravarty et al. (2014) extend customer orientation research by the important aspect that in more complex business models firms need to be customer oriented to more than just one customer population, their study does not

address the challenges raised by free e-services. First, free end users are profoundly important even without bringing in monetary returns. Previous research on customer value has demonstrated that free end users are more critical to the platform than paying B2B customers are, because they attract paying customers who do pay for the platform-based interaction (Gupta & Mela, 2008; Kraemer et al., 2010). Second, such interaction between free end users and paying B2B customers challenges providers in their customer orientation behaviors. Given these particularities of free e-services and the scarcity of studies in this context, in Study 1, we investigate managers' mental models of free e-services and how these mental models inform customer orientation behaviors.

5.3 Study 1: Qualitative Study—Mental Models of Free E-Services

Study 1 was a qualitative investigation in which we interviewed managers of free e-services. The research objective was to gain improved knowledge on providers' mental models of free e-services and how these mental models influence customer orientation behaviors.

5.3.1 Method.

We chose a qualitative exploratory research approach to investigate industry experts' mental models in the free e-services sector, which entailed interviewing 19 executives of German free e-service providers (Table 5.1). This is consistent with sample sizes recommended for exploratory research (Guest, Bunce, & Johnson, 2016). Our sampling procedure followed the approach of Strauss and Corbin (1990), thus we stopped sampling at the point of saturation. The interviews of between 40 and 75 minutes each were recorded and transcribed verbatim. They were conducted in a semi-structured format, using an initial set of prepared questions to guide the interviews (e.g., Who is the customer in your free e-service? What is the free end user's role for your business model? How do you manage free end users?), with

specific follow-up questions based on each informant's individual response. For analysis, we open-coded the transcripts according to methods by Boyatzis (1998) and Braun and Clarke (2006) using MAXQDA. To identify topics relevant to our research goals, two researchers independently open-coded the transcripts. The results were compared, jointly discussed and matched with existing literature. Interview findings are either displayed as direct quotes or paraphrased. After each quote, explicit reference is given in parantheses to the interviewee and to the paragraph in the verbatim transcript of the interview.

Table 5.1. List of interview participants Study 1

Interview	Function	Business Field	Number of Employees	Founded in
R1	General Manager	Publishing House (with Online Sector)	>200	1949
R2	General Manager	Online Community	10–49	2011
R3	General Manager Digital	Publishing House (with Online Sector)	50–199	2001
R4	General Manager	Online Career Network	10–49	2000
R5	General Manager	Online Community	10–49	2010
R6	Marketing Manager	Real Estate Marketplace	>200	1997
R7	General Manager	Online Community	<10	2009
R8	General Manager	Software Provider	50–199	2003
R9	Head of Operations	Online Community	10–49	2002
R10	General Manager	Online Community	10–49	2012
R11	Marketing Manager	Couponing App Provider	10–49	2009
R12	General Manager	Tariff Consultancy	<10	2012
R13	Marketing Manager	Online Community	50–199	2006
R14	General Manager Digital	Publishing House (with Online Sector)	>200	1946

R15	Marketing Manager	Price Comparison Website	>200	1999
R16	General Manager	Price Comparison Website	>200	1999
R17	Head of Strategy	Online Marketplace (Real Estate, Cars)	>200	1993
R18	General Manager	Price Comparison Website	50–199	1999
R19	General Manager	Publishing House (with Online Sector)	>200	1974

5.3.2 Results.

5.3.2.1 Free end users' superiority and customer orientation toward free end users.

In accordance with our theoretical assumptions, our interviews showed that providers are aware of the high importance of free end users for free e-services. Thus, providers aim to offer free end users superior value by means of customer orientation. Even though managers perceive both customer populations—free end users as well as paying B2B customers—as vital to their business (R4, para. 10; R11, para. 45; R17, para. 8), they acknowledge free end users as indispensable. Free e-services' business model does not work without free end users as they are "the key component of the business model" (R19, para. 23). Providers recognize the need to serve them with highly attractive service offers for delivering high value. As one respondent, a manager of a price comparison website, states: "It is of high importance, if we do not serve them [free end users] with high value, they will not return to our business" (R15, para. 10). Similarly, a manager of a mobile couponing-platform notes, that the highest risk to the success of its free e-service are limitedly attractive coupon offerings. Further, providers make use of customer orientation to create value for free end users. Respondents report their offerings to be heavily based on free end users' needs (R5, para. 51; R8, para. 78; R18, para. 20). Relatedly, some providers go a step further by bringing unfinished products to the market: "From the beginning, our purpose was not to have a fully developed

platform to bring to the market, but rather to go online with a raw product, which we would refine based on customers' priorities" (R10, para. 30). As a source of identifying users' needs, providers make use of free end users' explicitly communicated feedback (R6, para. 40; R7, para. 85), their behavioral online data (R3, para. 102; R5, para. 53; R10, para. 34), free end users' satisfaction surveys (R4, para. 86) or by using the Net Promoter Score (R6, para. 40). Our interviews make apparent that providers align the extent of customer orientation behavior toward free end users with the value this customer population brings to the providers' business. Therefore, providers prioritize the needs and expectations of highly valued[1] free end users over the needs of users with lower value. Even though they are critical to the business model's success, providers are not driven solely by free end users' articulated needs and interests in their customer orientation behavior. In this respect, a manager of an online community describes its customer orientation behavior toward free end users as follows: "Well yes, regarding stability, that means we do not chase every issue, this would just be impossible and lead to contorted maneuvers, because we have a huge community. Some people want things that other people don't. But we take it seriously and manage it. However, we still need to remain true to ourselves and stick to our platform" (R13, para. 174).

5.3.2.2 Interdependencies and customer orientation.

Our interview data reveals important findings in terms of customer orientation and interdependencies between customer populations in a platform setting. Our results provide evidence for managers' awareness of the interdependencies of both customer populations they have to serve; that is, managers take into account the impact customer orientation activities toward a focal population have on the other population. Relatedly, one interviewee, a manager of an online marketplace which

[1] Providers assess the value of free end users based on a ratio between revenues and the number of free end users (e.g., R7, para.16) or based on non-monetary values free customers provide such as their online activity (R9, para. 57; R13, para. 14).

brings together so-called listers (paying B2B customers) and searchers (free end users) states: “If it comes to pricing issues, you obviously focus on the listers. However, we always bear in mind, that our business model relies on the searchers” (R17, para. 8). Similarly, a manager of a career marketplace, which connects highly qualified students (i.e., free end users) to paying B2B customers, is aware of potentially negative effects of being overfocused on the interests of paying B2B customers. For example, a major strategic focus on firms’ interest in recruiting highly attractive students, carries the risk of lowering satisfaction among other students that are less attractive to the firms (R4, para. 70). In line with these findings, managers of advertising-based platforms are also aware that an overfocus on advertisers (i.e., paying B2B customers), for instance in terms of type and content of advertising provided on the platform, can diminish free end users’ satisfaction (R2, para. 75; R7, para. 52, 90; R18, para. 102). Vice versa, managers are aware that dedicated focus on free end users could diminish paying B2B customers’ satisfaction (R3, para. 114). The same is true in marketplaces, where, for instance, a manager of a pricing and service comparison platform, which arranges contracts between free end users and paying B2B customers, noted that free end users who repeatedly switch between energy suppliers, displease the suppliers: “You cannot tell a paying customer: ‘I have 100 new customers for you, but you know, next year 110 customers will leave you’, as it is likely if another paying customer comes up with a more attractive offer” (R12, para. 22).

5.3.2.3 Differences in mental models between free e-service providers.

Our interviews reveal first evidence that not all free e-service providers hold the same mental model of free e-services and subsequently differ in their customer orientation behaviors. This became evident in two interviews with managers of news platforms launched by established publishing houses who apparently are dissatisfied with the free business model (R1, para. 25). The managers are aware of

their free end users' importance to the business model, and thus of the importance of creating value for them (R1, para. 77; R1, para. 21, 147). Simultaneously, however, those managers substantially focus on their paying B2B customers' interests. A manager of a news portal stated, for example, that the strategic focus of his platform is on attracting as many free end users as possible, who are willing to react to advertisements of paying B2B customers by clicking on the ads or by buying something (R3, para. 115). Consequently, the mental orientation toward monetizing the service provider's offerings inhibits the alignment of their offerings to the needs of free end users. Even though such service providers have the required sense of how to shape offers that would better fulfill their free end users' needs, they do not act accordingly (R1, para. 79, 83). For instance, they indicate making use of advertising formats, even if they know this will prompt negative reactions among free end users (R1, para. 126-132). Further, the focus on monetizing perpetuates limited knowledge of free end users (R1, para. 51), and of how to efficiently and effectively fulfill their needs. For instance, one manager reports that the news platform assumes free end users to be homogeneous and similar to readers of the printed news, while in fact, they cannot be certain about it as they lack sufficient knowledge of their free end users (R3, para. 51, 60). This means that such service providers are unable to recognize different segments of free end users, and accordingly cannot align customer orientation behavior to free end users' value (R3, para. 32-33).

5.3.3 Discussion.

The purpose of Study 1 was to gain insight into providers' mental models of free e-services and of how these mental models influence customer orientation behaviors. Our findings corroborate and enrich previous research on customer orientation in multi-sided markets. As such, the results show that providers should not only attach importance to free end users in their marketing activities as

suggested by Gupta and Mela (2008), but that they indeed do so by being customer oriented toward them. Thus, our findings reveal that the traditional concept of customer orientation (Jaworski & Kohli, 1993; Narver & Slater, 1990) can be transferred to customer populations that do not provide monetary value to a firm. Thereby, free end users' management is similar to what firms do in more traditional market settings with paying customers only. Providers strongly focus on value-based customer orientation behavior, to efficiently and effectively address free end users' needs. Most interestingly, our interviews yield new insights on how free e-service providers deal with the interdependencies reigning in multi-sided markets in their customer orientation behaviors. Free e-service providers always bear in mind the effects customer orientation activities have on both customer populations, i.e., not only on the population which is presently in the focus of customer orientation activities, but also on its counterpart.

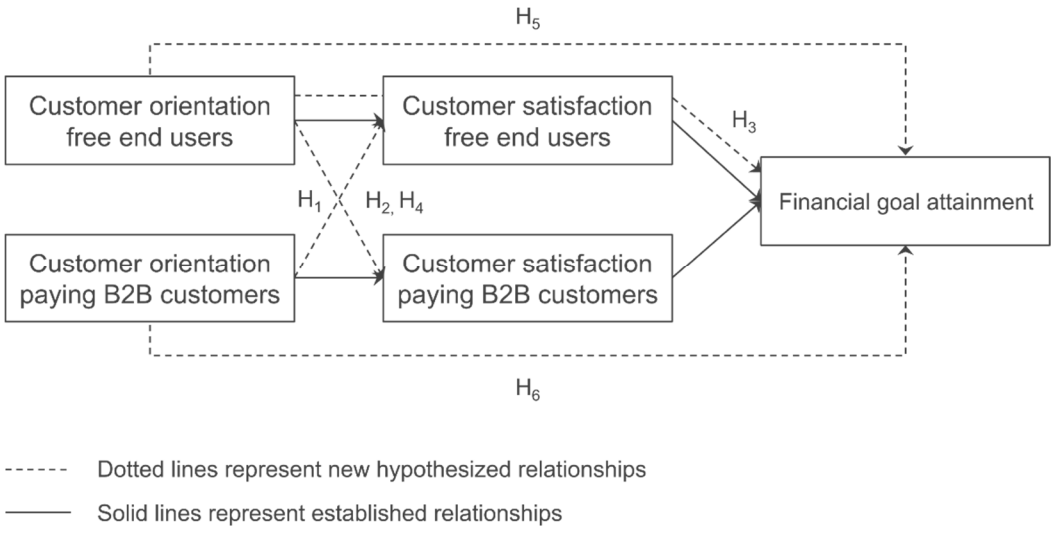
Notably, the two examples of news platforms indicate that firms' prior strategic commitments (Srinivasan & Moorman, 2005) influence providers' mental models of free e-services and subsequently their customer orientation behaviors and outcomes. Firms that build on a business model of end users' direct monetization prior to launching a free e-service (laggards) have more difficulties when adopting a free e-service, than firms that built on the free business model from the start (free-borns). Obviously, laggards rely on their past experiences in markets with paying customer groups only, which hinders them in developing an accurate mental model of free e-services. Laggards strongly emphasize the monetization of their offering and thereby fail to recognize the importance of free end users. These findings corroborate research which reveals that firms' different prior strategic commitments form different mental models, i.e., "simplified knowledge structures or cognitive representations about how the business environment works" (Gary & Wood, 2011, p. 569), which in turn guide managerial action (Leonard-Barton, 1992; Teece, Pisano, & Shuen, 1997). Based on their strategic commitments, firms

develop a “dominant logic” (Prahalad & Bettis, 1986) about the business reality and the necessary actions to take to reach their goals in this environment. However, this dominant logic hinders the accurate understanding of new business realities that are distinct from the firm’s original core business. Typically, firms try to fit the new business reality into their existing mental models (Danneels, 2003; Kanter, 2001; Prahalad & Bettis, 1986). Hence, firms develop an inaccurate understanding of the new business environment and its paradigms, and as such, they cannot take actions necessary for responding to the challenges of the new business context.

Drawing on our results and discussion of Study 1 and on evidence from previous literature, we develop the conceptual framework for Study 2 in the next section. The major aim of Study 2 is to show how free-borns’ and laggards’ different mental models of free e-services influence customer orientation behaviors and outcomes. Specifically, we investigate the influence a firm’s strategic commitment has on (a) providers’ ability to satisfy both customer populations while being customer oriented toward only one of those populations, and (b) on how customer orientation toward the populations impacts a provider’s financial goal attainment beyond the effect through free end users and paying B2B customers’ satisfaction.

5.4 Conceptual Framework and Hypotheses

Figure 5.2. Conceptual framework: The effects of customer orientation on customer satisfaction and financial goal attainment in free e-services



5.4.1 Cross-effects of customer orientation.

In this paragraph we focus on the effects of customer orientation toward the two customer populations on their respective satisfaction as depicted in our conceptual framework (Figure 5.2). Research widely acknowledges that by fulfilling the needs of a customer population through customer orientation, firms can increase the satisfaction of this customer population (Brady & Cronin, 2001; Slater & Narver, 1994). Study 1 further reveals that in the case of interdependencies between customer populations, customer orientation behavior toward one population can also prompt a positive impact on the satisfaction of the other population (dotted lines in Figure 5.2, H_1 and H_2). As our interviewees point out, providers are able to take into account the influence customer orientation behavior toward one customer population has on the other population's satisfaction, and vice versa. Accordingly, we expect them to shape customer orientation behaviors toward each of the customer populations in a way that satisfies both populations simultaneously. For instance, for advertising-based providers, this could translate into offering personalized content for free end users on the one hand which is also highly attractive for advertiser as they can target clearly defined free end user segments. On the other hand, personalized advertisments could be one possible manifestation of customer orientation toward paying B2B customers which simoultaneously satisfies free end users as it is more relevant and less annoying to them than standardized advertisments. Thus, we assume customer orientation toward free end users to have a positive impact on the paying B2B customers' satisfaction and customer orientation toward paying B2B customers to increase free end users' satisfaction. Satisfying both customer populations is of tremendous importance for providers' financial goal attainment as indicated by prior research. Satisfaction is an important driver of customer loyalty of both, free end users and paying B2B customers (E. Anderson & Sullivan, 1993). A platform with a higher number of free end users and paying B2B customers is, in turn, more attractive to potential other

members of the two customer populations due to direct and indirect network externalities (Gupta & Mela, 2008; Kraemer et al., 2010; Rochet & Tirole, 2006). Hence, not only paying customers will contribute to a provider's financial goal attainment as has been widely shown in customer orientation research. Also free end users that do not generate any direct revenues increase provider's financial goal attainment. Thus, we hypothesize:

H_1: Customer orientation toward free end users increases paying B2B customers' satisfaction.

H_2: Customer orientation toward paying B2B customers increases free end users' satisfaction.

H_3: Customer orientation toward free end users increases the financial goal attainment of providers through free end users' and paying B2B customers' satisfaction.

Based on the interview results, however, we expect only free-borns to fully exploit the potential of customer orientation in free e-services. Their mental model of free e-services enables them to leverage the interdependencies between free end users and paying B2B customers to satisfy both customer populations simultaneously by being customer oriented toward only one population. The satisfaction of both customer populations, in turn, contributes directly and indirectly to a provider's financial performance as outlined in the previous paragraph. Laggards, in contrast, are not likely to exploit the benefits of customer orientation to the same extent. Our interviews indicated that laggards developed a mental model that product and service offers need to be directly reimbursed. This mental model hinders them to fully acknowledge the importance of free end users, as previous research in this area has shown that mental models guide managerial cognition and action (Leonard-Barton, 1992; Teece et al., 1997). We expect laggards to shape their customer orientation behavior accordingly: Due to the strong focus on monetization, laggards have in mind paying B2B customers' satisfaction when being customer oriented toward free end users. However, they are not aware of free end

users' needs to the same extent as free-borns are when being customer oriented toward paying B2B customers. Thus, customer orientation toward free end users will increase paying B2B customers' satisfaction. Yet, the increase in free end users' satisfaction through customer orientation toward paying B2B customers will be lower for laggards than for free-borns. Thus, laggards cannot benefit from the full potential of the interdependencies in free e-services. Following our reasoning, we hypothesize:

> H_4: A provider's prior strategic commitment moderates the positive impact of customer orientation toward paying B2B customers on free end users' satisfaction, such that customer orientation toward paying B2B customers increases free end users' satisfaction to a greater extent for free-borns than for laggards.

5.4.2 Customer orientation efficiency and effectiveness.

In this paragraph, we focus on the direct dotted path between customer orientation toward free end users and the provider's financial goal attainment as depicted in Figure 5.2. Research has shown that firms incur considerable costs with customer orientation and customer-oriented behaviors. Lee, Sridhar, Henderson, and Palmatier (2014) demonstrate that customer-centric firms can increase their long-term financial performance through higher satisfaction of their customers. However, the authors also show that customer-centric structures increase firms' costs which, in turn, negatively affect their performance.

According to the results of our interviews, we expect free-borns, in total, to be able to reduce those cost effects of customer orientation as they align the value they create through customer orientation to the value they receive from free end users. Free-borns segment free end users based on their value (e.g., through segmenting free end users according to their activity on the provider's platform) and adjust their customer orientation behavior accordingly. Research has highlighted the benefits of such customer value-based marketing for the long-term success of customer-firm-relationships (Kumar & Reinartz, 2016), as customer value-based

marketing is both, effective and efficient. In this respect, Homburg, Droll, and Totzek (2008) demonstrate that such customer prioritization strategies increases customers' average satisfaction with the firm and simultaneously decreases firms' marketing and sales costs.

Our interviews reveal that laggards, in contrast, treat all free end users equally and do not segment them based on their value to the platform. Accordingly, the level of customer orientation behavior is the same for all free end users, and consequently, laggards cannot realize efficiencies through segmentation. We thus expect customer orientation behavior toward free end users to be less efficient for laggards than for free-borns. Inefficiencies can be fueled further by the realization of diseconomies of scope. Due to their prior experiences, routines and assets for customer orientation are based on paying customer populations. As such, customer orientation behavior toward free end users needs either to refer to those existing routines and assets or laggards need to acquire assets and develop new routines, specifically, for customer orientation toward free end users. Both instances will deteriorate the financial goal attainment of free e-service providers through costly conflicts (Bresnahan, Greenstein, & Henderson, 2011) or high investments (Greenstein, 2017).

In summary, we hypothesize:

> H_5: A provider's prior strategic commitment moderates the effect of customer orientation toward free end users on a provider's financial goal attainment, such that the negative impact of customer orientation toward free end users on a provider's financial goal attainment is smaller for free-borns than for laggards.

Further, we expect inefficiencies and ineffectiveness for laggards when they are customer oriented toward paying B2B customers (dotted direct path between customer orientatation to paying B2B customers and financial goal attainment in Figure 5.2), even if laggards are accustomed to paying customer populations

through their experiences in the initial business with only paying end consumers. As outlined before, laggards perceive paying B2B customers as very powerful and believe them to be most important for the platform's success. We know from previous research that a firm's customer orientation behavior toward powerful customers is mainly characterized by a tight connection between firms. This tight connection translates into firms mainly fulfilling customers' articulated needs (Danneels 2003). However, it simultaneously inhibits laggards' proactive shaping of the relationship with paying B2B customers, e.g., by identifying potential new customers or paying B2B customers' latent needs, each of which are positively correlated with a provider's performance. Further, laggards mostly allocate too many resources to paying B2B customers, thus creating additional inefficiencies (Christensen & Bower, 1996; Danneels, 2003). Free-borns, in contrast, are more loosely connected to paying B2B customers. Although free-borns are aware of paying B2B customers' relevance for subsidizing the provider's offer to free end users, they know that, in the end, free end users are critical for the platform's success. Thus, free-borns will not necessarily fulfill all articulated needs of paying B2B customers, but be more active in shaping the relationship with them by also addressing their latent needs, or identifying new segments of potential paying B2B customers (Danneels, 2003). Therefore, we assume that, more than laggards, free-borns will create additional benefits from customer orientation behavior toward paying B2B customers, besides just satisfying them. Hence, we hypothesize the following:

H_6: A provider's strategic commitment moderates the effect of customer orientation toward paying B2B customers on a provider's financial goal attainment, such that the positive impact of customer orientation toward free end users on a provider's financial goal attainment is higher for free-borns than for laggards.

5.5 Study: Quantitative Study—Outcomes of Customer Orientation

5.5.1 Method.

5.5.1.1 Sample selection and data collection.

To test the proposed conceptual model empirically, we conducted a cross-sectional online survey with key informants of free e-service providers in Germany. We compiled a database of providers, as there are no existing databases available with purely free e-services. In order to identify e-services, we conducted a thorough search, by turning to different sources, namely AGOF, a German association of online marketers, and IVW, the Information Community for the Assessment of the Circulation of Media. Further, we searched through online and offline outlets of business newspapers to identify additional free e-services relevant to our database. Moreover, we advertised our research project on professional social networks sites. We contacted every provider included in our database by phone to locate willing and knowledgeable informants. In total, our prequalified database consisted of 722 free e-services that received our survey.

Having identified providers and their key informants, we sent each a personal login for the online survey. We first explained the purpose of the study. To incentivize participation, we provided the option of receiving a benchmark report. Also, we offered a €25 gift card for each completed survey. We used three screening questions at the beginning of our survey to ensure only free e-service providers with a two-sided market structure participate in the survey. We asked key informants whether their service offering is directed at private end users (instead of business customers) and whether the e-service is free for the majority of users. To increase the response rate, we sent a reminder about the survey after four weeks. In all, 95 key informants participated in the study, yielding a response rate of 13.2%.

5.5.1.2 Measures.

To differentiate between free-borns and laggards, we assessed a service provider's prior strategic commitment to the free business model. In doing so, we relied on the operationalization provided by Srinivasan and Moorman (2005). This measure included questions about the year of firm founding and the year in which the firm launched the free e-service. We then calculated the difference in years, and coded providers which started with the free business model from the beginning (i.e., no difference between years of founding and launch) as 1, and those who did not with 0.[2] We measured customer orientation toward free end users and paying B2B customers separately using Narver and Slater's (1990) original scale. Its applicability for measuring customer orientation in two-sided markets was demonstrated by Chakravarty et al. (2014). The scale included the following items: "Our business objectives are driven primarily by the satisfaction of free end users [paying B2B customers]," "We constantly monitor our level of commitment and orientation to serving the needs of free end users [paying B2B customers]," "Our strategy for competitive advantage is based on our understanding of the needs of free end users [paying B2B customers]," "Our business strategies are driven by our beliefs about how we can create greater value for free end users [paying B2B customers]," "We measure the satisfaction of free end users [paying B2B customers] systematically and frequently" and "We give close attention to customer service for free end users [paying B2B customers]." Similar to customer orientation, customer satisfaction was measured separately for both customer populations, using a three-item scale from Vorhies and Morgan (2005). We asked key informants how well providers did in satisfying their customer populations, in delivering value to them and in delivering what they want compared to similar offerings of competitors. A similar scale by Vorhies and Morgan (2005) was used to assess a provider's financial goal

[2] We analyzed our results with an alternative operationalization that calculated the difference between founding and launch greater than one year. Those analyses yielded the same results in magnitude, direction and significance of the effects.

attainment. Managers were asked to assess how well they performed financially compared to their competitors. We used this subjective single-item measure to ensure that we could compare different free e-services in different stages of their business lifecycle which have different strategic objectives (i.e., growing their platform, being profitable). Kirca et al. (2005) demonstrated that in customer orientation research single-item performance measures yield similar results to multi-item performance measures.

5.5.1.3 Control variables.

We included several covariates in our analysis. Following prior conceptualizations studying the outcomes of customer orientation, we included measures for both firm size and firm age in our questionnaire (Hult, Ketchen, & Slater, 2005). We assessed firm size by the number of employees working specifically for the free e-service. Finally, we differentiated between small providers with one to nine employees (= 0), and large providers with more than nine employees (= 1). Firm age was measured as the difference in years between 2016 (when data collection was completed) and the date of firm founding, which we then log-transformed. We included a provider's revenue model as a last covariate. A revenue model specifies how platform firm's generate revenues in a given business model (Amit & Zott, 2001). We classified providers into two groups according to the indicated revenue model, assessing whether the paying B2B customers' content is part of the platform's value-proposition to free end users (1 = Content integration), or not (= 0). This is the case for brokerage affiliates, like TripAdvisor, where advertised hotels constitute the unique selling proposition to free end users. In the case of advertising-based revenue models, paying B2B customers' content (e.g., ads) is distinct from the platform's value proposition to free end users (e.g., news).[3]

[3] Further types of revenue models that do not integrate paying B2B customers' offering into the value proposition to free end users encompass the selling of free end user data to paying B2B customers or providers conducting marketing research for paying B2B customers.

5.5.1.4 Sample description.

The final sample consisted of 53 free-borns and 38 laggards. As outlined in Table 5.2 and Table 5.3, there are no differences in the providers' characteristics except for a provider's funding and its revenues.[4] Free-borns and laggards offer the same type of free e-service, refer to similar types of revenue models, have on average the same age and employ a similar number of employees. Based on the definition of laggard firms as ones that followed a non-free business model prior to launching a free e-service, it seems intuitive that free e-services are cross-subsidized by a firm's additional offers to a greater extent than free-borns, as they possibly adopted the free e-service as additional firm offering besides non-free ones.

[4] With revenues, we refer to a firm's total revenues, i.e., including the revenues of additional offers, may they refer to the free business model or not.

Table 5.2. Sample characteristics Study 2

	Free-Borns in %	**Laggards** in %	**χ^2-Test**
Revenue Model			
Brokerage Affiliate	60	63	$\chi^2(1, N = 91) = 0.003$
Advertising	91	84	$\chi^2(1, N = 91) = 0.349$
Marketing Research	4	8	$\chi^2(1, N = 91) = 0.148$
Data selling	13	3	$\chi^2(1, N = 91) = 1.909$
Category			
News	36	37	$\chi^2(1, N = 91) = 0.000$
Entertainment	36	39	$\chi^2(1, N = 91) = 0.018$
Advice	23	45	$\chi^2(1, N = 91) = 4.011$*
Social networks/communication	28	24	$\chi^2(1, N = 91) = 0.063$
Services	21	32	$\chi^2(1, N = 91) = 0.860$
Travel, weather and navigation	15	26	$\chi^2(1, N = 91) = 1.120$
Economy, finance and classified markets	15	18	$\chi^2(1, N = 91) = 0.018$
Sport and fitness	13	16	$\chi^2(1, N = 91) = 0.002$
Shopping/Catalogues	13	8	$\chi^2(1, N = 91) = 0.211$
Games	9	11	$\chi^2(1, N = 91) = 0.000$
Food and drinking	4	8	$\chi^2(1, N = 91) = 0.148$
Funding			
Bootstrapping	47	32	$\chi^2(1, N = 91) = 1.042$
Equity parent company	15	32	$\chi^2(1, N = 91) = 2.612$
Subsidies other company's offers	8	37	$\chi^2(1, N = 91) = 10.195$***
Business angel	13	16	$\chi^2(1, N = 91) = 0.002$
Venture capital	13	5	$\chi^2(1, N = 91) = 0.803$
Subsidies parent company	6	13	$\chi^2(1, N = 91) = 0.757$
Bank credit	9	5	$\chi^2(1, N = 91) = 0.114$
Public financing	8	5	$\chi^2(1, N = 91) = 0.000$
Crowdfunding	2	8	$\chi^2(1, N = 91) = 0.740$
Shares	0	0	$\chi^2(1, N = 91) = 2.473$
Revenues (in thousands of €)			$\chi^2(5, N = 79) = 11.815$*
< 100	43	31	
100 < 1,000	36	19	
1,000 < 5,000	11	28	
5,000 < 10,000	0	6	
10,000 < 50,000	11	9	
> 50,000	0	6	
Free end users (in thousands)			$\chi^2(5, N = 87) = 3.850$
< 10	5	10	
10 < 50	27	16	
50 < 250	30	22	
250 < 1,000	14	24	
1,000 < 10,000	19	24	
> 10,000	5	4	

Note. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5.5.1.5 Measure validation.

To assess the reliability of our measurement model, we refer to partial least squares structural equation modeling (PLS-SEM), using the software SmartPLS 3 (Ringle, Wende, & Becker, 2015). Using PLS-SEM to estimate structural equation models has recently expanded in top tier marketing journals and complements the use of covariance-based estimation techniques (CB-SEM). PLS-SEM is proven to be especially suitable in cases where sample sizes are below 250, as it yields more accurate estimates than CB-SEM (Hair, Sarstedt, Ringle, & Mena, 2012). Table 5.3 shows that all our constructs meet the necessary reliability and validity criteria. The average variance extracted is above the threshold of 0.50 (Bagozzi & Yi, 1988), and the alphas exceed 0.70 (Nunnally, 1978). Further, constructs have discriminant validity, as each construct's square root of the average variance extracted exceeds its bivariate correlations with all other constructs (Fornell & Larcker, 1981).[5]

5.5.1.6 Response and non-response biases.

Referring to single source data with only one key informant for each free e-service could question the accuracy of our assessed variables of interest. However, Homburg, Klarmann, Reimann, and Schilke (2012) point out that the accuracy of key informants' estimates depends on the specific constructs used in a study, informants' personal characteristics, and organizational characteristics. They demonstrate that the more present-focused the study's constructs are, the more constructs assess objective information; also, the more salient constructs are to a firm, the higher key informants' accuracy. Further, a key informant's hierarchical position and the R&D intensity positively influence accuracy, whereas accuracy decreases with increasing organization size and industry concentration. Turning to

[5] We could show discriminant validity also based on the Heterotrait-monotrait ratio (HTMT) as suggested by Henseler, Ringle, and Sarstedt (2015).

our conceptual framework, with customer orientation, customer satisfaction and a provider's competitive advantage, we assess constructs that are present-focused, salient to the provider, and have objective referents, at least for customer satisfaction and a firm's competitive advantage. Moreover, as 89% of the respondents have an executive position, and 64% of all providers in the sample employ nine or less employees, we are confident that inaccuracy in responses due to single-source data is not of concern in this study.

Furthermore, we tested our measurement model for common method variance (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). We assessed common method variance using the marker variable approach proposed by Lindell and Whitney (2001), a common technique for PLS-SEM estimations (Sattler, Völckner, Riediger, & Ringle, 2010; Wunderlich, Kranz, Totzek, Veit, & Picot, 2013). Including a marker variable in our structural model, did not yield any changes in our results. Thus, we are confident that our findings are not subject to common method bias, and our estimated path coefficients and significances are reliable.

Non-response bias is another concern in survey-based research. Therefore, we split our respondents' data into thirds, based on the time distance between the date we sent out the survey and the time we received it. We then compared the answers of the first third with the last third, expecting the latter to resemble non-respondents (J. Armstrong & Overton, 1977). Group comparisons yielded no significant differences, thus there is no evidence for non-response bias.

Table 5.3. Summary statistics, correlations and reliability criteria

									Strategic commitment		
									Free-Borns	Laggards	
	1	2	3	4	5	6	7	8	M (*SD*)	M (*SD*)	*t*-Value
1. Customer orientation FU	**0.76**	*0.15*	*0.37*	*0.22*	*0.12*	-	-	-	5.27 (1.07)	5.14 (1.25)	*t*(87) = -0.544
2. Customer orientation PC	0.03	**0.77**	*0.13*	*0.43*	*0.19*	-	-	-	4.67 (1.31)	4.68 (1.42)	*t*(88) = 0.019
3. Customer satisfaction FU	0.34***	0.12	**0.91**	*0.26*	*0.22*	-	-	-	5.49 (1.04)	5.68 (0.98)	*t*(87) = 0.901
4. Customer satisfaction PC	0.20†	0.39***	0.24*	**0.92**	*0.36*	-	-	-	5.38 (1.20)	5.00 (1.47)	*t*(86) = -1.357
5. Financial goal attainment	-0.12	0.18†	0.22*	0.34***	**1.00**	-	-	-	4.61 (1.22)	4.65 (1.58)	*t*(86) = 0.137
6. Firm age (log)	-0.30**	-0.01	-0.20*	0.08	0.19†	-	-	-	2.05 (0.85)	2.07 (0.86)	*t*(89) = 0.106
7. Firm size (1 = large)	-	-	-	-	-	-	-	-	0.37 (0.49)	0.29 (0.46)	*t*(87) = -0.814
8. Revenue model (1 = Content integration)	-	-	-	-	-	-	-	-	0.60 (0.49)	0.63 (0.49)	*t*(89) = 0.266
Cronbach's alpha	0.85	0.86	0.90	0.91	-	-	-	-			
Composite reliability	0.89	0.90	0.94	0.94	-	-	-	-			
AVE	0.58	0.59	0.83	0.85	-	-	-	-			

Note. $N = 95$; FU = free end users, PC = paying B2B customers; diagonal elements represent square root of AVE; lower off-diagonal elements represent bivariate correlations between metric variables; higher off-diagonal elements represent average item-correlations between two constructs to determine the Heterotrait-Monotrait Ratio (HTMT).
† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5.5.2 Results.

Table 5.3 displays correlations, means, and standard deviations for the constructs included in our conceptual framework. All constructs have weak to moderate correlations (r_{max} = 0.39), suggesting no problems of multicollinearity. The Variance Inflation Factors (VIF) of our structural model further confirm this suggestion. The variance inflation factors lie between VIF_{min} = 1.07 and VIF_{max} = 1.41, which is well beyond the critical value of 10 as suggested by Hair et al. (2014). Analyzing the mean values of our central constructs reveals that providers exhibit higher customer orientation to free end users than to paying B2B customers ($M_{CO,FU}$ = 5.22 vs. $M_{CO,PC}$ = 4.66), confirming our idea of the superiority of free end uses. The difference in means is significant ($t(91) = 3.017$, $p = 0.003$). Looking at the differences of both customer orientations for free-borns and laggards separaterly, we find evidence that only free-borns prioritize free end users over B2B paying customers in their customer orientation levels ($M_{CO,FU,FB}$ = 5.27 vs. $M_{CO,PC,FB}$ = 4.67, $t(50) = 2.535$, $p = 0.014$; $M_{CO,FU,LAG}$ = 5.14 vs. $M_{CO,PC,LAG}$ = 4.68, $t(36) = 1.478$, p = 0.148). This descriptive finding is a first indication that laggards do not acknowledge the superiority of free end users.

5.5.2.1 Cross-effects of customer orientation.

We referred to PLS-SEM, using SmartPLS 3, to test our subsequent hypotheses. We used 10,000 bootstrapping samples to assess the significance of our results (see Table 5.4), no sign changes were allowed. We imputed missing values by mean replacement. To test for group differences in paths between free-borns and laggards, we applied the Multi-Group Analysis of SmartPLS 3 (Table 5.5).

Looking at our results in Table 5.4 and Table 5.5, our analysis first supports customer orientation effects established in prior literature. It yields a significant positive link between customer orientation to free end users and their satisfaction (p_1 = 0.324, $p = 0.003$) as well as for customer orientation to paying B2B customers and

their satisfaction (p_2 = 0.325, p = 0.002). Turning to our proposed cross effects of customer orientation, we find support for H_1. Customer orientation to free end users exhibits a significant positive effect on paying customers' satisfaction (p_3 = 0.212, p = 0.048). However, customer orientation toward paying B2B customers does not increase end users' satisfaction significantly (p_4 = 0.142, p = 0.278), as proposed in H_2. In line with previous research, the satisfaction of both free end users and paying B2B customers, in turn, exhibit a significant positive impact on the provider's financial goal attainment (p_5 = 0.262, p = 0.004; p_6 = 0.282; p = 0.009). In consequence, we find support for H_3 that hypothesized the positive indirect effect customer orientation to free end users has on the provider's financial goal attainment through free end users' and paying B2B customers' satisfaction (p_9 = 0.145 p = 0.006).

As outlined in H_4, we find partial support for the moderating effect of providers' prior strategic commitment. For free-borns, customer orientation to paying B2B customers leads to significant higher satisfaction of free end users ($p_{4,FB}$ = 0.322, p = 0.064). For laggards, customer orientation to paying B2B customers has no significant effect on free end users' satisfaction ($p_{4,LAG}$ = -0.061, p = 0.736). The difference in the path coefficients is significant (Δp_4 = 0.384, p = 0.070). This moderating effect explains why we did not find support for H_2 for the overall sample.

5.5.2.2 Customer orientation efficiency and effectiveness.

In the second part of our conceptual framework, we hypothesized that free-borns and laggards differ in the efficiency and effectiveness of customer orientation behavior. For this reason, we compare the direct effects of customer orientation to free end users and paying B2B customers on the providers' financial goal attainment for free-borns and laggards through multi-group comparisons. In doing so, we find support for H_5, and partial support for H_6. For laggards, customer orientation to free end users significantly diminishes their financial goal attainment ($p_{7,LAG}$ = -0.587,

p = 0.001). For free-borns, in contrast, customer orientation to free end users does not influence the provider's financial performance ($p_{7,FB}$ = -0.038, *p* = 0.786). This difference is significant (Δp_7 = 0.549, *p* = 0.010), in that the provider's prior strategic commitment moderates the effect of customer orientation to free end users on the provider's financial goal attainment. With regard to H_6, our analysis provides evidence that free-borns reap additional benefits from customer orientation to paying customers beyond its effect on the financial goal attainment through paying customers' satisfaction. Customer orientation to paying customers directly increases a free-born's financial goal attainment ($p_{8,FB}$ = 0.397, *p* = 0.012). For laggards, however, customer orientation to paying B2B customers does not yield any additional benefits besides satisfying them ($p_{8,LAG}$ = -0.218, *p* = 0.336). The difference in path coefficients between free-borns and laggards is significant (Δp_8 = 0.615, *p* = 0.022). The provider's prior strategic commitment moderates the effect of customer orientation to paying B2B customers on the provider's financial goal attainment.

Table 5.4. SmartPLS estimation results full model

Hypothesized paths			*b*	*SE*	*t*-value	*p*-value
Cross-effects of customer orientation						
p_1: Customer orientation FU	→	Customer satisfaction FU	0.324**	0.110	2.947	0.003
p_2: Customer orientation PC	→	Customer satisfaction PC	0.325**	0.104	3.142	0.002
p_3: Customer orientation FU	→	Customer satisfaction PC	0.212*	0.110	1.974	0.048
p_4: Customer orientation PC	→	Customer satisfaction FU	0.142	0.131	1.084	0.278
p_5: Customer satisfaction FU	→	Financial goals	0.262	0.091	2.888	0.004
p_6: Customer satisfaction PC	→	Financial goals	0.282	0.108	2.618	0.009
Customer orientation efficiency and effectiveness						
p_7: Customer orientation FU	→	Financial goals	-0.226†	0.124	1.824	0.068
p_8: Customer orientation PC	→	Financial goals	0.028	0.129	.221	0.825
Indirect effects of customer orientation						
p_9: Customer orientation FU	→	Financial goals	0.145**	0.052	2.767	0.006
p_{10}: Customer orientation PC	→	Financial goals	0.129*	0.058	2.235	0.025
Controls						
Firm age	→	Customer satisfaction FU	-0.081	0.118	0.694	0.488
Firm age	→	Customer satisfaction PC	0.081	0.095	0.861	0.389
Firm age	→	Financial goals	0.133	0.127	1.043	0.297
Firm size	→	Customer satisfaction FU	-0.129	0.102	1.262	0.207
Firm size	→	Customer satisfaction PC	0.235**	0.089	2.641	0.008
Firm size	→	Financial goals	0.065	0.105	0.620	0.535
Revenue model	→	Customer satisfaction FU	-0.077	0.099	0.780	0.435
Revenue model	→	Customer satisfaction PC	0.033	0.093	0.357	0.721
Revenue model	→	Financial goals	0.001	0.093	0.010	0.992

Note. $N = 95$; FU = free end users, PC = paying B2B customers.
† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5.5. Results MGA-analysis with free-borns and laggards

	Strategic commitment				
	Free-borns		Laggards		Difference in Path coefficients
Moderated path	*b*	*SD*	*b*	*SD*	Δb
p_3: Customer orientation FU → Customer satisfaction PC	0.237	(0.174) $^{n.s.}$	0.219	(0.198)$^{n.s}$	0.018$^{n.s.}$
p_4: Customer orientation PC → Customer satisfaction FU	0.322	(0.174) †	-0.061	(0.181)$^{n.s.}$	0.384†
p_7: Customer orientation FU → Financial goals	-0.038	(0.140) $^{n.s.}$	-0.587	(0.178)**	0.549*
p_8: Customer orientation PC → Financial goals	0.397	(0.158) *	-0.218	(0.227)$^{n.s.}$	0.615*

Note. N = 95; FU = free end users, PC = paying B2B customers.
† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

In H_6, we argued that free-borns generate higher additional benefits through customer orientation to paying B2B customers, as their customer orientation behavior is less driven by perceptions of paying B2B customers' power than it is for laggards. Consequently, free-borns are more loosely connected to paying B2B customers, and can shape the relationship by addressing existing paying B2B customers' articulated and latent needs. Moreover, they are able to identify potential new segments of paying B2B customers. Additional survey data support this argumentation. We assessed the perceived power of paying B2B customers based on Agle, Mitchell, and Sonnenfeld (1999) Agle, Mitchell, and Sonnenfeld (1999)'s measure. Regressing customer orientation to paying B2B customers on their perceived power, yields the following results: Whereas free-borns' customer orientation to paying B2B customers is not driven by the perceived power of paying B2B customers ($p_{POW,FB}$ = -0.165, p = 0.243), perceived power does influence laggards' customer orientation significantly ($p_{POW,LAG}$ = 0.298, p = 0.082). The higher laggards perceive the power of paying B2B customers, the higher is their customer orientation to them. This difference is significant (Δp_{POW} = 0.938, p = 0.001).

5.5.3 Additional analysis.

To further test whether laggards are less performant than free-borns, we conducted an additional analysis based on our survey data. Research on business models demonstrates that firms' intention to change their business model is a direct reaction to performance shortfalls (Osiyevskyy & Dewald, 2015). Assuming laggards to be less performant than free-borns based on the results of Study 2, this would suggest that laggards are more likely to switch to a different revenue model than free-borns. In our survey, we included a question that asked participants to state whether they wanted to change their revenue model in the near future. Thus, we performed a simple chi-square test to determine whether free-borns were more likely to stick to their current revenue model than laggards. Indeed, we found support for this assumption. The chi-square test is significant ($\chi^2(1, N = 91) = 5.429$, $p = 0.020$), confirming that a firm's intention to change its revenue model is not independent of its prior strategic commitment. Of the laggards in our sample, 53% that answered the respective survey question intended to change their revenue model. Free-borns, though, seem to be satisfied with their revenue model, as only 26% of those platform firms (14 out of 53) stated that they would change their revenue model in the near future. This result further confirms the difficulties laggards have with regard to the free business model.

5.6 General Discussion

The results of Study 1 and 2 demonstrate that free-borns possess a more accurate mental model of free e-services than laggards. As a consequence, their customer orientation behavior better matches the requirements of free e-services and, thus, free-borns can serve free end users' and paying B2B customers' needs more effectively and efficiently than laggards. Free-borns' customer orientation behavior allows them to satisfy both customer populations while being customer oriented to only one of the populations. Thereby, higher customer orientation to free

end users does not yield higher costs, as free-borns align the extent of their customer orientation behavior to the value free end users offer them. Customer orientation to paying B2B customers even yields additional financial benefits, as providers proactively shape their relationship with paying B2B customers. Laggards' mental model, in contrast, overemphasizes the importance of paying B2B customers for free e-services, which hinders their ability to leverage the full potential of customer orientation. Though they are customer oriented toward free end users to the same extent as free-borns, they are unable to satisfy free end users' needs when being customer oriented toward paying B2B customers. Further, laggards' customer orientation behavior is highly driven by paying B2B customers' perceived power. Moreover, they do not segment free end users in terms of value. This results in inefficient and ineffective customer orientation behavior of laggards.

5.6.1 Theoretical contributions.

Our findings make several theoretical contributions, specifically to the two important marketing research fields of customer orientation and two-sided markets.

5.6.1.1 Contribution to research on customer orientation.

Our contributions to research on customer orientation are three-fold: First, our findings expand existing knowledge about customer orientation in two-sided markets by applying a disaggregated perspective on customer orientation. In contrast to Chakravarty et al. (2014), who investigated the effects of two aggregated measures of customer orientation, namely total customer orientation and asymmetric customer orientation, we investigated customer orientation to each customer population separately, and assessed their individual outcome effects. Our results demonstrate that, in two-sided markets, firms can leverage customer orientation to one customer population to satisfy not only the focal population, but also the other one. Looking at the underlying mechanism with the help of our

qualitative interview data, we identified an important capability of platform firms: Providers are aware of the potential impact of customer orientation behavior toward one customer population on the satisfaction of the other population and vice versa, which allows them to satisfy both populations at once. As, in turn, the customer populations' satisfaction helps providers to reach their financial goals, customer orientation to both free end users and paying B2B customers, contributes to providers' financial performance. This finding suggests that the well-established link between customer orientation and firm performance in traditional markets with only one customer population (Jaworski & Kohli, 1993; Kirca et al., 2005; Narver & Slater, 1990) is also applicable to each of the customer populations in two- or multi-sided markets.

Second, we show that customer orientation is necessary, even toward customer populations that do not provide any monetary value. This extends prior research looking at bi- and multilateral value exchanges between customers and firms that focused solely on paying customers (Chakravarty et al., 2014; Jaworski & Kohli, 1993; Narver & Slater, 1990). We find evidence that being customer oriented to free end users influences a provider's financial performance, as long as they interact with paying instances. Customer orientation toward free end users increases paying B2B customers' satisfaction, which in turn directly contributes to a provider's revenues (E. Anderson & Sullivan, 1993). Further, due to network externalities, satisfying free end users by means of customer orientation to them, contributes to a provider's financial performance. Satisfied free end users have a higher propensity to stick with the provider, thereby rendering it more attractive to potential new paying B2B customers. New paying B2B customers, then again, generate new revenues (Zhang, Evgeniou, Padmanabhan, & Richard, 2012).

Third, we disclose a firm's prior strategic commitment as a contingency factor of customer orientation, by showing that it influences providers' customer orientation behavior and customer orientation outcomes. Existing research on

customer orientation, instead, focusses mainly on exogenous factors that affect the link between customer orientation and a firm's performance, as for example, market or environment turbulence, technological turbulence, competitive intensity (Jaworski & Kohli, 1993; Kirca et al., 2005) or, in the case of two-sided markets, the market concentrations of both market sides (Chakravarty et al., 2014). Our findings highlight that also firm-internal factors influence the outcomes of customer orientation. Only firms that committed themselves to the free business model from the beginning, leverage the full potential of customer orientation. Free-borns have developed a mental model that matches the particularities of free e-services, i.e., the criticality of free end users, and the interdependencies between free end users and paying B2B customers. Thus, they leverage customer orientation behavior to one customer population to satisfy both customer populations at once. In contrast, laggards have difficulties to fully capture the importance of free end users. They apply customer orientation behavior to them and satisfy them, as well as paying B2B customers. However, they do not take into account free end users' satisfaction when being customer oriented toward paying B2B customers. Further, the data reveals that laggards are too tightly connected to the articulated interests of paying B2B customers, which in turn leads to ineffectiveness and inefficiency in their customer orientation behavior toward them. As for free-borns, customer orientation to paying B2B customers yields additional financial benefits besides the financial gain already generated through the satisfaction of paying B2B customers.

5.6.1.2 Contributions to research on two-sided markets.

First, we add meaningful insights to research on two-sided markets by identifying customer orientation as an appropriate coordination strategy for a provider's sustainability. Platform firms' main interest lies in attracting and bonding both market sides to the platform in order to be successful (Rochet & Tirole, 2006). Due to the interaction of both market sides, platform firms simultaneously need to

coordinate the expectations of both market sides (S. Anderson & Gabszewicz, 2006; M. Armstrong, 2006; Eisenmann et al., 2006). Whereas previous research in this regard highlights pricing mechanisms (M. Armstrong, 2006; Caillaud & Jullien, 2003; Rochet & Tirole, 2006), as well as platform content (S. Anderson & Gabszewicz, 2006; Hagiu & Spulber, 2013; Wilbur, 2008) as important marketing strategies, our results emphasize the specific role of customer orientation in two-sided markets. We demonstrate that customer orientation is an appropriate mechanism coordinating both customer populations. Customer orientation toward one population simultaneously fulfills expectations of the same and the other customer population. However, providers need to consider the impact customer orientation behavior toward one customer population has on the satisfaction of the other population. In this regard, we provide additional evidence that marketing activities directed at advertisers as one manifestation of paying B2B customers, not necessarily have a negative impact on the satisfaction of free end users as highlighted by prior research (Wilbur, 2008).

Second, we show that the level of customer orientation to free end users is higher than to paying B2B customers, even if the former do not provide revenue. This finding makes an important contribution to our knowledge on two-sided markets with a free end user population. By modelling the customer value of free end users, previous studies showed that free end users are highly valuable to providers, and that providers therefore should assign more importance to them in their marketing activities (Gupta & Mela, 2008; Kraemer et al., 2010; Zhang et al., 2012). Our results extend these findings by confirming that providers are actually aware of free end users' value, and indeed assign high importance to them.

Third, we contribute to research on free e-services by showing that a provider's prior strategic commitment influences the success of free e-services. Our results demonstrate that free-borns stick to the free business model to a greater extent than laggards, as they have a more accurate mental model of free e-services.

Consequently, free-borns show appropriate customer orientation behaviors which contribute to their financial performance. Thus, our results indicate that an accurate understanding of how to respond to the particularities of free e-services with customer orientation, enables laggards to turn the free business model into a successful one. Extant research investigating this question mainly focused on freemium pricing strategies, where a part of the offer is not free to end users (Lambrecht & Misra, 2016; Pauwels & Weiss, 2008).

5.6.2 Managerial implications.

Our results provide meaningful and actionable implications for free e-service providers. First, the results of both studies demonstrate that customer orientation is necessary and valuable for reaching one's own financial goals in the context of free e-services. Providers need to be customer oriented to free end users and paying B2B customers. Providers must be especially aware of the critical role of customer orientation to free end users: Due to direct and indirect network externalities, customer orientation toward free end users indirectly contributes to a provider's success by attracting new free end users and paying B2B customers. Hence, it is as important for providers to fulfill the needs of free end users as it is to meet those of paying B2B customers.

Second, providers should leverage the interdependencies inherent in free e-services. Customer orientation behavior toward one customer population, can be used not only to satisfy this customer population, but also, simultaneously, the other population. To do so, providers need to develop a new capability: At any point when they are customer oriented toward one customer population, providers should be aware of the consequences their activities have on the other population's satisfaction. By anticipating those effects, providers can shape customer orientation behavior toward one customer population in a way that satisfies both population at once. Developing such customer orientation capabilities is an organization-wide task

which needs the top management's support and appropriate coordinating of customer orientation activities toward free end users and paying B2B customers, e.g., through centralization or a steady knowledge flow if customer orientation is decentralized. Developing such capabilities also requires training of employees, and the adjustment of key performance indicators (Jaworski & Kohli, 1993).

Third, our results will prove to be especially valuable for laggards, i.e., for providers who had non-free business models prior to launching a free e-service. Even if they are customer oriented to free end users to the same extent as free-borns, laggards still need to deepen their understanding of free e-services to accurately inform their customer orientation behaviors. Only then, they will know how to positively leverage the particularities of free e-services, to render customer orientation behavior toward free end users and paying B2B customers effectively and efficiently. Most importantly, providers should be aware of the criticality of free end users. They not only need to be customer oriented toward free end users directly, but also have to keep their interests in mind when they are customer oriented toward paying B2B customers. Raising awareness for free end users' value implies shifting attention from key performance indicators which capture consumers' monetary value contributions only, to key performance indicators that also include non-monetary value contributions, such as word-of-mouth, co-production, network effects, attention, or data (Anderl, März, & Schumann, 2016). Further, customer orientation toward free end users and paying B2B customers needs to be more efficient and effective. Regarding customer orientation toward free end users, laggards should align their customer orientation behavior to the value free end users have to the service provider. Additionally, they should recognize that customer orientation behavior is different for free end users and paying B2B customers. For instance, the needs of paying B2B customers could be assessed directly through key account managers, whereas this is hardly actionable with free end users due to their large numbers. Text-mining and online-surveys could be a valuable alternative.

Regarding customer orientation toward paying B2B customers, laggards should be cautious not to only fulfill their obvious and articulated needs, but also to proactively shape the relationship with paying B2B customers by addressing their latent needs. To do so, laggards must understand the subordinate importance of paying B2B customers for the free business model. Changing a company's mental model and developing new capabilities, as in the case of laggards, is challenging, as it implies investments throughout the whole organization (Leonard-Barton, 1992; Teece et al., 1997). For example, the top management has to allocate sufficient resources for the organization to build an adequate knowledge base about free e-services, and to adapt organizational routines and processes to the particularities of free e-services. However, our results provide evidence that those investments pay-off, as providers then are enabled to leverage the full potential of customer orientation in free e-services.

5.6.3 Limitations and future research.

The limitations of our study provide fruitful avenues for further research. First, we assessed the outcomes of customer orientation (i.e., free end users' and paying B2B customers' satisfaction and provider's financial performance) based on the perceptions of one single key informant. Future research should identify additional data sources to validate our findings. Besides using survey data from managers of free e-services, future research could additionally build on survey data of free end users as well as of paying customers. These data sources would add further perspectives as, for instance, customers' perception of customer orientation behavior targeted toward them. Furthermore they would deliver a more reliable measurement of the customer populations' satisfaction. Nevertheless, following Homburg et al. (2012), we are confident that our results yield first valuable insights into customer orientation and its outcomes in free e-servcies. For instance, they point out that information's accuracy is high, if respondents are asked about salient

constructs, if they have an executive position or if they are employed in small firms, as it is the case in our study. Second, validating the impact customer orientation toward free end users has on financial performance, is another promising research issue. However, this might be a challenging task, as many small and young firms identify as free e-service providers who are not required to disclose their financial data publicly. An alternative to this approach could be to run a longitudinal study to determine firm survival and success, which is a common approach in research on market entry timing (Kalyanaram, Robinson, & Urban, 1995), closely related to our measure of a provider's strategic commitment. Third, and related to this, additional research is needed that will analyze the impact of customer orientation on different performance indicators. In this research, we focused on a firm's financial goal attainment to be able to compare the providers of our sample. However, providers pass distinct phases throughout their business life-cycle, with distinct strategic goals. While the growth of free end users and paying B2B customers is of particular interest at the beginning of the life-cycle, at later stages providers focus on the platform's profitability. Future research could examine whether considering the needs of one customer population while being customer oriented toward another population, has equal positive effects on distinct strategic goals. Fourth, another promising area for in-depth future research is the provider's capability taking into account the effects customer orientation toward one customer population has on the other population's satisfaction. In this respect, we argue, that free-borns leverage this capability better than laggards do. We propose the underlying reason is that free-borns acknowledge the needs of both customer populations, while laggards are too heavily tied to paying B2B customers and their needs. However, this proposition requires empirical validation. As such, future research could use experimental studies with managers, in order to analyze whether the dedicated focus on paying B2B customers in their experience with non-free business models, causes laggards to neglect the interests of free end users while being customer oriented toward

paying B2B customers. Fifth, analyzing additional moderators or sub-groups among free-borns and laggards could yield new interesting and valuable insights. For instance, future research could disclose whether particular free-borns cope better with the free business model than others do. For laggards, it would be worthwhile to investigate whether laggards' inaccurate mental models of free e-services can be compensated for by other capabilities.

5.7 Conclusion

Extant conceptions of customer orientation are not sufficient to explain how the particularities of free e-services (i.e., superiority of free end users, interdependencies between both populations) influence customer orientation behaviors and outcomes in free e-eservices. Using two studies, we have demonstrated that providers possess different mental models of those particularities and, thus, also differ in customer orientation behaviors and their outcomes. Free-borns, who strategically committed themselves to the free business model from the beginning, possess an accurate model of free e-services' particularities and are therefore able to create value for free end users and paying B2B customers efficiently and effectively. In contrast, laggards who committed themselves to non-free business models prior to launching a free e-service, in contrast, are inefficient and ineffective in their customer orientation behavior as they underestimate the importance of free end users, and overestimate that of the paying B2B customers. We suppose this to be the underlying reason why laggards are finding it difficult to adjust to the free business model.

5.8 References

Agle, B. R., Mitchell, R. K., & Sonnenfeld, J. A. (1999). Who matters to CEOs? An investigation of stakeholder attributes and salience, corporate performance, and CEO values. *The Academy of Management Journal*, *42*, 507–525. https://doi.org/10.5465/256973

Amit, R., & Zott, C. (2001). Value creation in e-business. *Strategic Management Journal*, *22*, 493–520. https://doi.org/10.1002/smj.187

Anderl, E., März, A., & Schumann, J. H. (2016). Nonmonetary customer value contributions in free e-services. *Journal of Strategic Marketing*, *24*, 175–189. https://doi.org/10.1080/0965254X.2015.1095219

Anderson, E., & Sullivan, M. W. (1993). The antecedents and consequences of customer satisfaction for firms. *Marketing Science*, *12*, 125–143. https://doi.org/10.1287/mksc.12.2.125

Anderson, S., & Gabszewicz, J. J. (2006). Chapter 18—The media and advertising: A tale of two-sided markets. In V. A. Ginsburg & D. Throsby (Eds.), *Handbook of the economics of art and culture* (pp. 567–614). Elsevier. https://doi.org/10.1016/S1574-0676(06)01018-0

Armstrong, J., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, *14*, 396–402. https://doi.org/10.2307/3150783

Armstrong, M. (2006). Competition in two-sided markets. *The RAND Journal of Economics*, *37*, 668–691. Retrieved from http://www.jstor.org/stable/25046266

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, *16*, 74–94. https://doi.org/10.1007/BF02723327

Boyatzis, R. E. (1998). *Transforming qualitative information: Thematic analysis and code development*. Thousand Oaks, Calif.: SAGE Publications.

Brady, M. K., & Cronin, J. J. (2001). Customer orientation effects on customer service perceptions and outcome behaviors. *Journal of Service Research*, *3*, 241–251. https://doi.org/10.1177/109467050133005

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*, 77–101. https://doi.org/10.1191/1478088706qp063oa

Bresnahan, T., Greenstein, S., & Henderson, R. (2011). *Schumpeterian competition and diseconomies of scope; illustrations from the histories of Microsoft and IBM*, Harvard Business School, Boston.

Caillaud, B., & Jullien, B. (2003). Chicken & egg: Competition among intermediation service providers. *The RAND Journal of Economics*, *34*, 309–328. https://doi.org/10.2307/1593720

Chakravarty, A., Kumar, A., & Grewal, R. (2014). Customer orientation structure for internet-based business-to-business platform firms. *Journal of Marketing*, *78*, 1–23. https://doi.org/10.1509/jm.12.0442

Christensen, C. M., & Bower, J. L. (1996). Customer power, strategic investment, and the failure of leading firms. *Strategic Management Journal*, *17*, 197–218. https://doi.org/10.1002/(SICI)1097-0266(199603)17:3<197::AID-SMJ804>3.0.CO;2-U

Danneels, E. (2003). Tight–loose coupling with customers: the enactment of customer orientation. *Strategic Management Journal*, *24*, 559–576. https://doi.org/10.1002/smj.319

The Economist. (2015). Up against the paywall. Retrieved from https://www.economist.com/news/business/21678799-many-publishers-still-see-little-alternative-continual-cutbacks-up-against-paywall

Eisenmann, T., Parker, G., & van Alstyne, M. W. (2006). Strategies for two-sided markets. *Harvard Business Review*, *84*, 92–101.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*, 39–50. https://doi.org/10.2307/3151312

Gary, M. S., & Wood, R. E. (2011). Mental models, decision rules, and performance heterogeneity. *Strategic Management Journal*, *32*, 569–594. https://doi.org/10.1002/smj.899

Greenstein, S. (2017). The reference wars: Encyclopædia Britannica's decline and Encarta's emergence. *Strategic Management Journal*, *38*, 995–1017. https://doi.org/10.1002/smj.2552

Guest, G., Bunce, A., & Johnson, L. (2016). How many interviews are enough?: An experiment with data saturation and variability. *Field Methods*, *18*, 59–82. https://doi.org/10.1177/1525822X05279903

Gupta, S., & Mela, C. F. (2008). What is a free customer worth? Armchair calculations of nonpaying customers' value can lead to flawed strategies. *Harvard Business Review*, *86*, 102–109.

Hagiu, A., & Spulber, D. (2013). First-Party content and coordination in two-sided markets. *Management Science*, *59*, 933–949. https://doi.org/10.1287/mnsc.1120.1577

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, *40*, 414–433. https://doi.org/10.1007/s11747-011-0261-6

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of*

the Academy of Marketing Science, *43*, 115–135. https://doi.org/10.1007/s11747-014-0403-8

Homburg, C., Droll, M., & Totzek, D. (2008). Customer prioritization: Does it pay off, and how should it be implemented? *Journal of Marketing*, *72*, 110–130. https://doi.org/10.1509/jmkg.72.5.110

Homburg, C., Klarmann, M., Reimann, M., & Schilke, O. (2012). What drives key informant accuracy? *Journal of Marketing Research*, *49*, 594–608. https://doi.org/10.1509/jmr.09.0174

Hult, G. T. M., Ketchen, D. J., & Slater, S. F. (2005). Market orientation and performance: An integration of disparate approaches. *Strategic Management Journal*, *26*, 1173–1181. https://doi.org/10.1002/smj.494

Jaworski, B. J., & Kohli, A. K. (1993). Market orientation: Antecedents and consequences. *Journal of Marketing*, *57*, 53–70. https://doi.org/10.2307/1251854

Kalyanaram, G., Robinson, W. T., & Urban, G. L. (1995). Order of market entry: Established empirical generalizations, emerging empirical generalizations, and future research. *Marketing Science*, *14*, G212-G221. https://doi.org/10.1287/mksc.14.3.G212

Kanter, R. M. (2001). The ten deadly mistakes of wanna-dots. *Harvard Business Review*, *79*, 91-100.

Kirca, A. H., Jayachandran, S., & Bearden, W. O. (2005). Market orientation: A meta-analytic review and assessment of its antecedents and impact on performance. *Journal of Marketing*, *69*, 24–41. https://doi.org/10.1509/jmkg.69.2.24.60761

Kraemer, T., Hinz, O., & Skiera, B. (2010). Return on marketing investments in two-sided markets. Retrieved from http://www.anzmac2010.org/proceedings/pdf/anzmac10Final00236.pdf

Kumar, V., & Reinartz, W. (2016). Creating enduring customer value. *Journal of Marketing*, *80*, 36–68. https://doi.org/10.1509/jm.15.0414

Lambrecht, A., & Misra, K. (2016). Fee or free: When should firms charge for online content? *Management Science*, *63*, 1150–1165. https://doi.org/10.1287/mnsc.2015.2383

Lee, Ju-Yeon, Sridhar, S., Henderson, C., & Palmatier, R. W. (2014). Effect of customer-centric structure on long-term financial performance. *Marketing Science*, *34*, 250–268. https://doi.org/10.1287/mksc.2014.0878

Leonard-Barton, D. (1992). Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal*, *13*, 111–125. https://doi.org/10.1002/smj.4250131009

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology*, *86*, 114–121. https://doi.org/10.1037/0021-9010.86.1.114

Narver, J. C., & Slater, S. F. (1990). The effect of a market orientation on business profitability. *Journal of Marketing*, *54*, 20–35. https://doi.org/10.2307/1251757

Nunnally, J. (1978). *Psychometric theory* (Vol. 2). New York: McGraw-Hill.

Osiyevskyy, O., & Dewald, J. (2015). Inducements, impediments, and immediacy: Exploring the cognitive drivers of small business managers' intentions to adopt business model change. *Journal of Small Business Management*, *53*, 1011–1032. https://doi.org/10.1111/jsbm.12113

Pauwels, K., & Weiss, A. (2008). Moving from free to fee: How online firms market to change their business model successfully. *Journal of Marketing*, *72*, 14–31. https://doi.org/10.1509/jmkg.72.3.14

Podsakoff, P., MacKenzie, S. B., Lee, Jeong-Yeon, & Podsakoff, N. (2003). Common method biases in behavioral research: A critical review of the literature

and recommended remedies. *Journal of Applied Psychology*, *88*, 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Prahalad, C. K., & Bettis, R. A. (1986). The dominant logic: A new linkage between diversity and performance. *Strategic Management Journal*, *7*, 485–501. https://doi.org/10.1002/smj.4250070602

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). SmartPLS 3. Bönningstedt: SmartPLS. Retrieved from http://www.smartpls.com

Rochet, J.-C., & Tirole, J. (2006). Two-sided markets: A progress report. *The RAND Journal of Economics*, *37*, 645–667. https://doi.org/10.1111/j.1756-2171.2006.tb00036.x

Sattler, H., Völckner, F., Riediger, C., & Ringle, C. M. (2010). The impact of brand extension success drivers on brand extension price premiums. *International Journal of Research in Marketing*, *27*, 319–328. https://doi.org/10.1016/j.ijresmar.2010.08.005

Slater, S. F., & Narver, J. C. (1994). Market orientation, customer value, and superior performance. *Business Horizons*, *37*, 22–28. https://doi.org/10.1016/0007-6813(94)90029-9

Srinivasan, R., & Moorman, C. (2005). Strategic firm commitments and rewards for customer relationship management in online retailing. *Journal of Marketing*, *69*, 193–200. https://doi.org/10.1509/jmkg.2005.69.4.193

Strauss, A. L., & Corbin, J. M. (1990). *Basics of qualitative research: Grounded theory procedures and techniques* (1. print). Newbury Park Calif. u.a.: SAGE Publications.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*, 509–533.

https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Van Alstyne, M. W., Parker, G., & Choudary, S. P. (2016). Pipelines, platforms, and the new rules of strategy. *Harvard Business Review*, *94*, 54–62.

Vorhies, D. W., & Morgan, N. A. (2005). Benchmarking marketing capabilities for sustainable competitive advantage. *Journal of Marketing*, *69*, 80–94. https://doi.org/10.1509/jmkg.69.1.80.55505

Wilbur, K. C. (2008). A two-sided, empirical model of television advertising and viewing markets. *Marketing Science*, *27*, 356–378. https://doi.org/10.1287/mksc.1070.0303

Wunderlich, P., Kranz, J., Totzek, D., Veit, D., & Picot, A. (2013). The impact of endogenous motivations on adoption of IT-enabled services. *Journal of Service Research*, *16*, 356–371. https://doi.org/10.1177/1094670512474841

Zhang, K., Evgeniou, T., Padmanabhan, V., & Richard, E. (2012). Content contributor management and network effects in a UGC environment. *Marketing Science*, *31*, 433–447. https://doi.org/10.1287/mksc.1110.0639

6. General Discussion

In four essays, I sought to answer my overarching research question on how free digital platforms' activities influence the value they create for their customer groups and the value they extract for themselves. In the following, I want to discuss the findings of my dissertation by outlining theoretical contributions to research on digital platforms and managerial implications that go beyond the individual contributions and implications of the four essays. The chapter concludes with an outlook on digital platforms.

6.1 Theoretical Contributions

6.1.1 Intrinsic value creation.

First, I expand existing research on two-sided markets by demonstrating that the creation of both extrinsic and intrinsic value is of major importance for platforms. Previous research focuses almost exclusively on platforms' extrinsic value creation, assessed by customer groups as the number of members of the same and other customer groups on the platform (Rochet und Tirole 2006; Caillaud und Jullien 2003; Gupta und Mela 2008). However, my dissertation shows that platforms also can create intrinsic value by providing their own resources to customer groups or coordinating the resources of their platform members (Hillebrand, Driessen, & Koll, 2015; Lee & O'Connor, 2003; van Alstyne, Parker, & Choudary, 2016). It demonstrates that any platform activities directed at one customer group influence the value creation of both that customer group and the other customer group. Studies 1 and 2, for example, show that Google features that allow firms to personalize and position their ads and adjust ad positions to consumers' previous online shopping behavior directly affect consumers' click and purchase decisions, because the outcomes of personalization and positioning are directly visible to consumers. Study 3 shows that tagging reviews as written on either mobile or nonmobile devices, with the objective of offering recipients a better understanding of

the context of review creation, influences value creation for both recipients and firms on the review platform. Study 4 generalizes the findings of Studies 1 to 3 by showing that any customer-oriented behavior of digital platforms toward one customer group influences the value creation of both this customer group and the other customer group. Digital platforms can extract maximum value from their customers only if their activities create value for *all* customer groups.

6.1.2 Superiority of non-paying customer groups.

Second, my dissertation reveals the peculiarity of non-paying customer groups in two-sided markets. Building on my first contribution, my findings demonstrate that value creation for non-paying customer groups is more important for digital platforms' value creation than is value creation for paying customer groups. As demonstrated by Studies 1 to 3, platforms create value for paying customers only if they create value for non-paying customers. Google (Studies 1 and 2) creates value if users click on personalized, well-positioned search ads and ultimately purchase from advertisers' online stores. Online review platforms create value for listed firms as well as advertisers if non-paying recipients perceive reviews as helpful. Only in this way will non-paying customers stick to platforms and make them attractive for paying customer groups. Accordingly, my findings demonstrate that the superiority effect of non-paying customer groups, which extant research has identified as key to digital platforms' extrinsic value creation, (Gupta & Mela, 2008; Kraemer, Hinz, & Skiera, 2010), also applies to platform activities that create intrinsic value.

Moreover, Study 4 shows that managers' cognitions about the value creation of non-paying customer groups are biased. In this way, I extend existing research on the zero-price effect, which to date has identified biased value perceptions at the consumer level only. This research has revealed that free offers lead to the overestimation of benefits and underestimation of costs, resulting in irrational high

demand for free offers (Shampanier et al. 2007; Hüttel et al. 2018). In addition, my findings on laggard firms demonstrate that free offers also entail biased value perceptions at the firm level. These firms, which in the past were accustomed to serving only paying customers, have difficulty understanding the importance of non-paying customer groups. In particular, laggards are not able to anticipate how platform activities directed at paying customer groups affect value creation for non-paying customer groups. Consequently, they fall short in designing their activities in such a way that they simultaneously create value for both paying and non-paying customer groups.

6.1.3 Boundary conditions of value creation and extraction.

Third, my dissertation contributes to previous research by identifying consumer preferences, technology, and firms' strategic commitments as important boundary conditions for digital platforms' value creation and extraction in all environmental contexts of digital platforms. Jaworski (1988) differentiates the internal, operating, and macro-environments in which firms operate. Extant research has focused exclusively on firms' operational environments, which encompass their customers and suppliers, among others; it has theoretically identified the influence of customer heterogeneity for value extraction in two-sided markets (C. Anderson, 2013; Armstrong, 2006; Caillaud & Jullien, 2003). In Studies 1 and 2, I find empirical support for the importance of customer heterogeneity. Study 1 shows that non-paying customer groups' value perceptions of personalizing and positioning search ads depends on whether advertisers (i.e., paying customer groups) decide uniformly to personalize their search ads. Study 2 demonstrates that heterogeneity in non-paying customers' preferences has a different impact on how they respond to ad positions on search engine results pages. Moreover, by considering consumers' technological devices and firms' prior strategic commitments, I expand research on two-sided markets by identifying two boundary conditions from digital platforms'

macro- and internal environments. For instance, Study 3 reveals that value creation on digital platforms hinges on the technological devices consumers use. Recipients consider online reviews useful only if the type of device with which they read the reviews matches the type of device with which reviewers created the reviews. Finally, Study 4 shows that internal firm factors influence value creation on digital platforms. Depending on a digital platform's past strategic decisions, the platform is more (free-born platforms) or less (laggards) able to create value for both customer groups and extract this value.

6.1.4 New methods and data in research on two-sided markets.

Fourth, I contribute to extant research on two-sided markets by broadening the spectrum of methods and data used to investigate two-sided markets. Most previous research has focused on theoretical structural models to examine a platform's extrinsic value creation or referred to modeling approaches to describe network externalities (Caillaud & Jullien, 2003; Chu & Manchanda, 2016; Gupta & Mela, 2008; Rochet & Tirole, 2006). Some studies also use survey data or experiments (Chakravarty, Kumar, & Grewal, 2014; Tucker & Zhang, 2010). In contrast, in my dissertation, I simultaneously adopt a variety of methods and thus create robust and compelling evidence of value creation and value extraction on digital platforms (Davis, Golicic, & Boerstler, 2011). In particular, Study 1 uses data from laboratory experiments; Study 2 combines a field experiment and observational data; Study 3 uses field data and laboratory experiments; and Study 4 makes use of qualitative and quantitative survey data.

6.2 Managerial Implications

The findings of my dissertation also have important implications for managers of free digital platforms.

6.2.1 Development of customer (retention) orientation.

In addition to generating extrinsic value by attracting enough members of both customer groups, digital platforms need to create intrinsic value for existing members by coordinating resources from their customer groups and providing resources to the customer groups. Digital platforms must develop a customer orientation and direct customer-oriented activities primarily toward existing members of the platform to retain those members at the platform (Arnold, Fang, & Palmatier, 2011; Chakravarty et al., 2014; Narver & Slater, 1990). Digital platforms must be capable of orienting their concrete activities to their customer groups' specific interests and needs. In this way, platforms can create value for their customer groups, as demonstrated by Study 4. Establishing a customer orientation implies the development of a corresponding corporate culture, alignment of platform strategies with the objective of retaining customers, measurement of relevant key performance indicators, corresponding reward systems and an active top management support among others (Arnold et al., 2011; Jaworski & Kohli, 1993; Narver & Slater, 1990).

6.2.2 Knowledge creation about free digital platforms and development of appropriate capabilities.

My findings also demonstrate that to develop appropriate management capabilities, managers of digital platforms must form knowledge about the inherent dynamics of digital platforms. Specifically, managers should understand how managerial actions directed at one customer group influence value creation of the other customer group, given that they are integrating the resources of both actors and making them available to each of the customer groups. In this regard, systems thinking gains importance (Hillebrand et al., 2015; van Alstyne et al., 2016). When designing their activities, managers always should anticipate the effect the activities will have on their customer groups' value perception and ultimately their own platforms' value extraction. This anticipation helps managers to create value for both customer groups and extract value for the platform itself.

Moreover, managers of free digital platforms must acknowledge the importance of non-paying customers. As Study 4 of my dissertation demonstrates, platforms should not focus exclusively on the monetary returns of their customer groups. Non-paying customer groups create value for digital platforms by interacting with customer groups that are willing to pay for this interaction; they thus provide revenues to digital platforms, but in an indirect way. For example, one way to raise managers' awareness of non-paying customers is to emphasize the non-monetary value contributions of such customers; non-paying customers are attentive to the advertising content of paying firms or provide data that digital platforms can sell either directly or indirectly through marketing research (Anderl, März, & Schumann, 2016). Acknowledging the particular importance of non-paying customers also means that digital platforms should reassess their relationships with paying customer groups. As my findings indicate, value creation for paying customers is a direct result of value creation for non-paying customers. In this way, paying customers are comparable to shareholders for whom value creation depends directly on value creation for customers (Agle, Mitchell, & Sonnenfeld, 1999; S. Anderson & Gabszewicz, 2006; Srivastava, Shervani, & Fahey, 1998). Thus, direct and exclusive value creation for paying customer groups is of secondary importance, and digital platforms should not seek to fulfill all or solely their needs and claims.

6.2.3 Focus on data collection and data analytics.

My findings reveal that the collection of (behavioral) data about individual customer groups and the analysis of these data are of enormous importance for digital platforms. Digital platforms should make use of the numerous possibilities for data collection in the digital era and develop suitable data analytics capabilities to make effective and efficient data-driven decisions (Wedel & Kannan, 2016). As Studies 1 to 3 show, by doing so, digital platforms can draw important conclusions

about customers' platform behavior, which make platforms' activities both more effective and efficient.

In addition to structured data, digital platforms should refer to unstructured data, such as text. As the interviews in Study 4 demonstrate, digital platforms can use textual data and corresponding analytics tools to identify the interests and needs of non-paying customers. This ability is crucial, because non-paying customers—and thus their needs and interests—often remain anonymous to the digital platform due to a lack of a formal relationship with the platform. Thus, textual data may be the sole source for assessing their needs and aligning platforms' value-creating activities. Digital platforms should make use of collected data to adapt their activities to the concrete environmental context too, in which the interaction between the customer groups takes place. As demonstrated by Studies 1 to 3, there are two reasons that this option constitutes the only way that digital platforms can create maximum value for both customer groups and extract maximum value for themselves. First, these data allow the identification of heterogeneity in customer behavior. Second, managers can use the data to reveal the technology used for the interaction, which informs the platforms' activities. Digital platforms such as Google already allow advertisers to segment consumers on the basis of their online shopping behavior in advertisers' online stores or the devices they are using, then adapt their search engine advertising strategies accordingly.

6.3 Outlook on Digital Platforms

The findings of my dissertation make important contributions to research on digital platforms. Yet, they also provide avenues for further research on digital platforms.

6.3.1 Business models of digital platforms.

In my studies, I emphasize the role of digital platforms as resource integrators. I investigate how the integration of resources of one customer group (e.g., personalized ads in search engines from advertisers) into offerings for other customer groups (e.g., search engine results page with personalized ads for end consumers) affects value creation for all actors on the digital platform. Researchers should build on this finding to examine how to integrate resources as a digital platform to maximize the value derived from customer groups. Study 4 of my dissertation proposes two central integration methods that researchers could investigate. On the one hand, one customer group's resources could coexist with the digital platform's value proposition toward other customer groups; this option is common in ad-financed business models, in which advertisers use the platform as medium to advertise their products and services (S. Anderson & Gabszewicz, 2006), but the ads are not part of a platform's content offerings (i.e., value proposition) to consumers. On the other hand, digital platforms could integrate one customer group's resources into their offerings to other customer groups, as is the case in marketplace business models. On Booking.com, hotels' resources (e.g., pictures and product descriptions) become part of the value proposition for consumers (e.g., information and booking). Research on advertising's negative effect on consumers' value perceptions (Wilbur 2008; Bleier und Eisenbeiss 2015) suggests that the second alternative (i.e., direct integration of one customer group's resources into the value proposition to the other customer group) may be more promising for digital platforms than the coexistence of resources and value propositions. Researchers should test these assumptions, as well as identify possible boundary conditions, to help answer the question of suitable business models for digital platforms (Lambrecht et al., 2014).

6.3.2 Non-paying customer groups and cognitive biases.

Another important avenue for research is to examine managers' cognitive biases in free digital platforms. Study 4 reveals that digital platform managers who previously were accustomed to paying end customers underestimate the importance of non-paying customers for their platforms' business models. As a result, they partly fail to acknowledge the interests of this customer group in their customer orientation behaviors. Researchers should analyze in greater depth whether the fact that non-paying customers provide no direct monetary revenues to the platform causes this cognitive bias. They might investigate whether the zero-price effect on end consumers on free digital platforms (Hüttel, Schumann, Mende, Scott, & Wagner, 2018; Shampanier, Mazar, & Ariely, 2007) also applies to managers of such platforms and whether its existence depends on platforms' prior strategic commitments. My results suggest that managers of laggard platforms, who are accustomed to paying end customers only, underestimate the value contributions of non-paying customers while overestimating the costs to serve these customer groups. Such a bias would imply a reversed zero-price effect for managers and identify platforms' prior strategic commitments as a first boundary condition. Researchers can test this argument, identify possible reasons, and seek evidence of other boundary conditions. Such studies would make significant contributions to extant marketing research that examines the impact of manager perceptions on firm performance (Day & Nedungadi, 1994; Mittal, Ross, & Tsiros, 2002; Rust, Moorman, & van Beuningen, 2016).

6.3.3 The impact of (mobile) technology.

I also call for further research on boundary conditions for value creation and value extraction on digital platforms. Researchers should focus on mobile technologies for digital platforms, because digital platforms increasingly are committing themselves to a "mobile first" strategy (Kloefkorn, 2018). First, we need

further evidence on the impact of platform activities on the value creation for customer groups, depending on which technology the groups use. Second, we need to know how digital platforms that exclusively work on mobile devices (i.e., apps) differ from nonmobile digital platforms in their ability to create and extract value. This research also could respond to existing calls for insights into which business models are best suited for mobile technologies (Lambrecht et al., 2014). Moreover, researchers could investigate how offering mobile and non-mobile digital platforms simultaneously affects digital platforms' value extraction. This line of research would be all the more interesting given that previous studies provide evidence of the effect of digital platforms on pricing, product, and promotion activities (Kraemer et al., 2010; Tucker & Zhang, 2010; Zhang, Evgeniou, Padmanabhan, & Richard, 2012) but have not investigated their influence on distribution activities, as the last element of the marketing mix. Finally, researchers might consider not only traditional mobile technologies (e.g., smartphones) but also wearables, such as smart watches or virtual glasses. Furthermore, the Internet-of-Things, in which static physical objects (e.g., cars, refrigerators, speakers) become digital platforms, as they are connected to their environments via wireless technologies and collect, exchange, and display information (Ng & Wakenshaw, 2017), offers entirely new avenues for research on the influence of technology on value creation and extraction on digital platforms.

6.3.4 Triangulation of data and longitudinal research designs.

From a methodological standpoint, researchers could make use of the multi-sidedness of digital platforms to collect data from digital platforms as well as from their customer groups. Such data triangulation would help validate the findings of my dissertation and offer the possibility of investigating research questions that are not possible to answer with data from only one source. For example, dyadic or triadic data allow researchers to identify perceptual differences between parties (Brown & Swartz, 1989; Davis et al., 2011). Researchers also should adopt longitudinal

research designs to assess the short- and long-term consequences of platform marketing activities. In particular, they might test how those activities affect relationships between customer groups and platforms, as well as paying customer groups' willingness to pay price premiums over time. By building on my findings from Studies 1 and 2, researchers could investigate the effect of search engine personalization and positioning features on advertisers' maximum bid levels, for example. With regard to review platforms (Study 3), researchers also could assess the effects of device tagging on readers' loyalty or willingness to create reviews.

6.4 References

Agle, B. R., Mitchell, R. K., & Sonnenfeld, J. A. (1999). Who matters to CEOs? An investigation of stakeholder attributes and salience, corporate performance, and CEO values. *The Academy of Management Journal*, *42*, 507–525. https://doi.org/10.5465/256973

Anderl, E., März, A., & Schumann, Jan H. (2016). Nonmonetary customer value contributions in free e-services. *Journal of Strategic Marketing*, *24*, 175–189. https://doi.org/10.1080/0965254X.2015.1095219

Anderson, C. (2013). *Free: How today's smartest businesses profit by giving something for nothing*. London: Random House.

Anderson, S., & Gabszewicz, J. J. (2006). Chapter 18—The media and advertising: A tale of two-sided markets. In V. A. Ginsburg & D. Throsby (Eds.), *Handbook of the economics of art and culture* (pp. 567–614). Elsevier. https://doi.org/10.1016/S1574-0676(06)01018-0

Armstrong, M. (2006). Competition in two-sided markets. *The RAND Journal of Economics*, *37*, 668–691. Retrieved from http://www.jstor.org/stable/25046266

Arnold, T. J., Fang, E., & Palmatier, R. W. (2011). The effects of customer acquisition and retention orientations on a firm’s radical and incremental innovation performance. *Journal of the Academy of Marketing Science*, *39*, 234–251. https://doi.org/10.1007/s11747-010-0203-8

Brown, S. W., & Swartz, T. A. (1989). A gap analysis of professional service quality. *Journal of Marketing*, *53*, 92–98. https://doi.org/10.2307/1251416

Caillaud, B., & Jullien, B. (2003). Chicken & egg: Competition among intermediation service providers. *The RAND Journal of Economics*, *34*, 309–328. https://doi.org/10.2307/1593720

Chakravarty, A., Kumar, A., & Grewal, R. (2014). Customer orientation structure for internet-based business-to-business platform firms. *Journal of Marketing*, *78*, 1–23. https://doi.org/10.1509/jm.12.0442

Chu, J., & Manchanda, P. (2016). Quantifying cross and direct network effects in online consumer-to-consumer platforms. *Marketing Science*, *35*, 870–893. https://doi.org/10.1287/mksc.2016.0976

Davis, D. F., Golicic, S. L., & Boerstler, C. N. (2011). Benefits and challenges of conducting multiple methods research in marketing. *Journal of the Academy of Marketing Science*, *39*, 467–479. https://doi.org/10.1007/s11747-010-0204-7

Day, G. S., & Nedungadi, P. (1994). Managerial representations of competitive advantage. *Journal of Marketing*, *58*, 31–44. https://doi.org/10.2307/1252267

Gupta, S., & Mela, C. F. (2008). What is a free customer worth? Armchair calculations of nonpaying customers' value can lead to flawed strategies. *Harvard Business Review*, *86*, 102–109.

Hillebrand, B., Driessen, P. H., & Koll, O. (2015). Stakeholder marketing: Theoretical foundations and required capabilities. *Journal of the Academy of Marketing Science*, *43*, 411–428. https://doi.org/10.1007/s11747-015-0424-y

Hüttel, B. A., Schumann, Jan Hendrik, Mende, M., Scott, M. L., & Wagner, C. J. (2018). How consumers assess free e-services: The role of benefit-inflation and cost-deflation effects. *Journal of Service Research*, *21*, 267–283. https://doi.org/10.1177/1094670517746779

Jaworski, B. J. (1988). Toward a theory of marketing control: Environmental context, control types, and consequences. *Journal of Marketing*, *52*, 23–39. https://doi.org/10.2307/1251447

Jaworski, B. J., & Kohli, A. K. (1993). Market orientation: Antecedents and consequences. *Journal of Marketing*, *57*, 53–70. https://doi.org/10.2307/1251854

Kloefkorn, S. (2018). Five things businesses must do to prepare for mobile-first indexing. Retrieved from https://www.forbes.com/sites/forbesagencycouncil/2018/07/19/five-things-businesses-must-do-to-prepare-for-mobile-first-indexing/#4afeb20a6820

Kraemer, T., Hinz, O., & Skiera, B. (2010). Return on marketing investments in two-sided markets. Retrieved from http://www.anzmac2010.org/proceedings/pdf/anzmac10Final00236.pdf

Lambrecht, A., Goldfarb, A., Bonatti, A., Ghose, A., Goldstein, D. G., Lewis, R., . . . Yao, S. (2014). How do firms make money selling digital goods online? *Marketing Letters*, *25*, 331–341. https://doi.org/10.1007/s11002-014-9310-5

Lee, Y., & O'Connor, G. C. (2003). New product launch strategy for network effects products. *Journal of the Academy of Marketing Science*, *31*, 241–255. https://doi.org/10.1177/0092070303031003003

Mittal, V., Ross, W. T., & Tsiros, M. (2002). The role of issue valence and issue capability in determining effort investment. *Journal of Marketing Research*, *39*, 455–468. https://doi.org/10.1509/jmkr.39.4.455.19122

Narver, J. C., & Slater, S. F. (1990). The effect of a market orientation on business profitability. *Journal of Marketing*, *54*, 20–35. https://doi.org/10.2307/1251757

Ng, I. C.L., & Wakenshaw, S. Y.L. (2017). The internet-of-things: Review and research directions. *International Journal of Research in Marketing*, *34*, 3–21. https://doi.org/10.1016/j.ijresmar.2016.11.003

Rochet, J.-C., & Tirole, J. (2006). Two-sided markets: A progress report. *The RAND Journal of Economics*, *37*, 645–667. https://doi.org/10.1111/j.1756-2171.2006.tb00036.x

Rust, R. T., Moorman, C., & van Beuningen, J. (2016). Quality mental model convergence and business performance. *International Journal of Research in Marketing*, *33*, 155–171. https://doi.org/10.1016/j.ijresmar.2015.07.005

Shampanier, K., Mazar, N., & Ariely, D. (2007). Zero as a special price: The true value of free products. *Marketing Science*, *26*, 742–757. https://doi.org/10.1287/mksc.1060.0254

Srivastava, R. K., Shervani, T. A., & Fahey, L. (1998). Market-based assets and shareholder value: A framework for analysis. *Journal of Marketing*, *62*, 2–18. https://doi.org/10.2307/1251799

Tucker, C., & Zhang, J. (2010). Growing two-sided networks by advertising the user base: A field experiment. *Marketing Science*, *29*, 805–814. https://doi.org/10.1287/mksc.1100.0560

Van Alstyne, M. W., Parker, G., & Choudary, S. P. (2016). Pipelines, platforms, and the new rules of strategy. *Harvard Business Review*, *94*, 54–62.

Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. *Journal of Marketing*, *80*, 97–121. https://doi.org/10.1509/jm.15.0413

Zhang, K., Evgeniou, T., Padmanabhan, V., & Richard, E. (2012). Content contributor management and network effects in a UGC environment. *Marketing Science*, *31*, 433–447. https://doi.org/10.1287/mksc.1110.0639

7. Conclusion

Free digital platforms are among the most important phenomena in modern times. Their peculiarity lies in the way they create value by bringing together two customer groups that would not have connected without digital technology or would have incurred increased costs for doing so. One of the two customer groups pays for the interaction; the other customer group uses the digital platform for free. Online newspapers, search engines, booking portals, and review platforms are just a few examples of platforms that bring end consumers together with advertisers, connect end consumers to hotels, or connect end consumers with end consumers and advertisers. Extant research provides rich evidence of how digital platforms can attract enough members of both customer groups to the platform to enable their interaction. However, this research lacks evidence about how free digital platforms can create value for existing customer groups through their activities and extract this value for themselves. In the current dissertation, I address this gap by conducting four studies. These studies investigate, on both concrete and abstract levels, how free digital platforms' activities affect value creation for customer groups and their ability to capture this value. My findings demonstrate that digital platforms can maximize value creation and their own value extraction if they design their activities to create value for both customer groups simultaneously. In particular, I determine that free digital platforms should focus on creating value for non-paying customer groups, because this value creation also creates value for paying customer groups. I also identify internal, operative, and macro-environments as important boundary conditions for value creation and extraction on free digital platforms. These findings make several substantial contributions to extant research on two-sided markets, customer orientation, search engine advertising, and online platforms; I also offer actionable implications for managers. In addition, my dissertation suggest numerous avenues for further research, which is of central importance to the growth of free digital platforms.